EXHIBIT 8

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MEASURING THE IMPLICATIONS OF SALES AND CONSUMER INVENTORY BEHAVIOR

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Temporary price reductions (sales) are common for many goods and naturally result in large increases in the quantity sold. Demand estimation based on temporary price reductions may mismeasure the long-run responsiveness to prices. In this paper we quantify the extent of the problem and assess its economic implications. We structurally estimate a dynamic model of consumer choice using two years of scanner data on the purchasing behavior of a panel of households. The results suggest that static demand estimates, which neglect dynamics, (i) overestimate own-price elasticities by 30 percent, (ii) underestimate cross-price elasticities by up to a factor of 5, and (iii) overestimate the substitution to the no-purchase or outside option by over 200 percent. This suggests that policy analysis based on static elasticity estimates will underestimate price–cost margins and underpredict the effects of mergers.

KEYWORDS: Long-run price elasticities, stockpiling, demand anticipation, discrete choice models, differentiated products, storable goods.

1. INTRODUCTION

WHEN GOODS ARE STORABLE, traditional static demand analysis is likely to mismeasure long-run own- and cross- price elasticities. A temporary price decrease may generate a large demand increase. However, if part of the increase is due to intertemporal substitution, then the (long-run) own-price response to a permanent price reduction would be smaller than static estimates suggest. On the other hand, the direction of the bias on cross-price elasticities is ambiguous. Static demand models are misspecified because they do not control for relevant history like past prices and inventories, and therefore estimates of price sensitivity might be biased. Even adding the right controls, static estimation confounds long- and short-run price effects. Measuring the long term response is relevant for most applications. For example, demand estimates are central in antitrust analysis and for computing welfare gains from new goods.

The distinction between long-run and short-run responses dates back to the Lucas and Rapping (1969) labor market study. Labor supply in their model responds to short-run wage changes differently than to long-run changes. In the context of product market demand estimation, most applications have neglected intertemporal effects (Bresnahan (1987), Hausman, Leonard, and Zona (1994), and Berry, Levinsohn, and Pakes (1995), as well as many others). Dynamic effects could be important, for example, for either durable or storable products. Previous work in the marketing and economics literature, which

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we survey below, documented purchasing patterns consistent with consumer stockpiling behavior. In an interesting paper, Erdem, Imai, and Keane (2003) study dynamic demand of a storable product (ketchup). The consumer inventory problem we study is very close to their setup. We propose a demand model that is computationally simpler and flexibly incorporates observable heterogeneity. The model enables us to split the estimation into a brand choice and a quantity choice. Most of the parameters are estimated consistently without solving the consumer's dynamic problem, and the remaining dynamic parameters are then estimated in a computationally simpler second stage.

We present a model in which households maximize the present expected value of future utility flows, facing uncertain future prices. In each period a household decides how much to buy, which brand to buy, and how much to consume. Quantities not consumed are stored, at a cost, and can be consumed in the future. The consumer balances the cost of holding inventory and potential future savings. The model is estimated using weekly scanner data on laundry detergents. These data were collected using scanning devices in nine supermarkets, belonging to different chains, in two submarkets of a large midwest city. In addition, we follow the purchases of households who shopped in those stores over a period of two years. The data have information on which product was bought, where it was bought, and how much was paid. It is also known when the households visited a supermarket but decided not to purchase a laundry detergent.

The structural estimation follows the nested algorithm proposed by Rust (1987). We have to make two adjustments. First, inventory, one of the endogenous state variables, is not observed by us. To address this problem we generate an initial distribution of inventory, and update it period by period using observed purchases and the (optimal) consumption prescribed by the model. Second, the state space includes prices (and promotional and advertising variables) of all brands in all sizes and therefore is too large for practical estimation. To reduce the dimensionality, we separate the probability of choosing any brand–size combination into the probability of choosing a brand conditional on the quantity purchased, and the probability of choosing each specific quantity. Given the stochastic structure of the model, we show that the probability of choosing a brand conditional on quantity does not depend on dynamic considerations. Therefore, we can estimate many of the parameters of the model without solving the dynamic programming problem. We estimate the remaining parameters by solving a nested algorithm in a much smaller space, considering only the quantity decision. This procedure enables us to estimate a general model, which allows for a large degree of consumer heterogeneity and nests standard static choice models. We discuss below the assumptions necessary to validate this procedure and the limitations of the method.

The estimates suggest that ignoring dynamics can have implications on demand estimates. Comparing estimates of the demand elasticities computed from a static model and the dynamic model, we find the following. First, the static model overestimates own-price elasticities by roughly 30 percent. Second,

the static model underestimates cross-price elasticities to other products. The ratio of the static cross-price elasticities to those computed from the dynamic model is as low as 0.2. Third, the estimates from the static model overestimate the substitution to the no-purchase or outside option by 200 percent.

Estimates of demand elasticities are typically used in a first-order condition, for example, of a pricing game, to compute price–cost margins (PCM). For single product firms, the magnitude of the bias of the implied margin is proportional to the bias in the own-price elasticities. Our findings suggest that for single product firms, the PCM computed from the dynamic estimates will be roughly 30 percent higher than those computed from static estimates. The bias is even larger for multiproduct firms because according to the dynamic estimates the products are closer substitutes than the static estimates suggest. Policy analysis based on static elasticity estimates will underestimate price–cost margins and underpredict the effects of mergers.

1.1. *Literature Review*

There are several empirical studies of sales in the economics literature. Pesendorfer (2002) studies sales of ketchup. In his model, he shows that the decision to hold a sale is a function of the duration since the last sale. His empirical analysis shows that both the probability of holding a sale and the aggregate quantity sold (during a sale) are a function of the duration since the last sale. Boizot, Robin, and Visser (2001) study dynamic consumer choice with inventory. They show that duration from previous purchase increases in current price and declines in past price, and quantity purchased increases in past prices. Hosken, Matsa, and Reiffen (2000) study the probability of a product being on sale as a function of its attributes. Aguirregabiria (1999) studies retail inventory behavior and its effect on prices.

The closest paper to ours is Erdem, Imai, and Keane (2003). They also structurally estimate a model of demand in which consumers can store different varieties of the product. To overcome the computational complexity of the problem, they make several simplifications that we discuss in detail in Section 4.3.3. Their estimation method is more computationally burdensome, but richer in unobserved heterogeneity. Our method, on the other hand, can handle patterns of observed heterogeneity more flexibly and, due to the computational simplicity, can handle a larger choice set. Erdem, Imai, and Keane study the role of price expectations. They compare consumers responses' to price cuts, both allowing for the price cut to affect future price expectations and holding expectations fixed. They also use the estimates to simulate consumer responses to short-run and long-run price changes. We compare the models in more detail in Section 4.

There is a vast literature in marketing that studies the effect of sales and its link to stockpiling (Shoemaker (1979), Blattberg, Eppen, and Lieberman (1981), Neslin, Henderson, and Quelch (1985), Currim and Schneider (1991),

Gupta (1988, 1991), Chiang (1991), Bell, Chiang, and Padmanabhan (1999)). Blattberg, Eppen, and Lieberman (1981) report that in the four categories they study the increase in duration to next purchase during sales is 23–36 percent. Neslin, Henderson, and Quelch (1985), using similar data, find acceleration of purchases for coffee and bathroom tissue as a reaction to advertised price cuts. Subsequent work (Currim and Schneider (1991), Gupta (1988, 1991)) finds effects of the same magnitude as Blattberg, Eppen, and Lieberman (1981). Neslin and Schneider Stone (1996), in surveying the literature, report estimates of purchase acceleration that range between 14 and 50 percent.

The more recent literature concentrates on decomposing consumers' response to sales. Gupta (1988) decomposes price responses into brand switching, acceleration of purchases, and stockpiling. In his coffee sample, 85 percent of the price response corresponds to brand switching, 14 percent is due to demand acceleration, and 2 percent relates to stockpiling. Chiang (1991) reports similar findings. Bell, Chiang, and Padmanabhan (1999) show that the primary demand expansion (the expansion in quantity sold in the category) is larger than the previous studies reported. Ailawadi and Neslin (1998) and Bell and Boztug (2004) study consumption effects to separate whether the sales expansions are caused by extra consumption or stockpiling. They report substantial consumption effects in their samples, explaining from 12 to 60 percent of increase in quantity sold.

2. DATA, INDUSTRY, AND PRELIMINARY ANALYSIS

2.1. *Data*

We use a scanner data set collected by Information Resources Inc. (IRI) from June 1991 to June 1993 that has two components: store-level and household-level data. The first data were collected using scanning devices in nine supermarkets, belonging to different chains, in two separate submarkets in a large midwest city. From the store-level data we know for each detailed product (brand–size) in each store in each week the price charged, (aggregate) quantity sold, and promotional activities. The second component of the data set is at the household level. We observe the purchases of households over a two year period. We know when a household visited a supermarket and how much they spent in each visit. The data include purchases in 24 different product categories for which we know which product each household bought, where it was bought, and how much was paid.

Table I displays statistics of some household demographics, laundry detergent purchases (the product we focus on below), and store visits in general. The typical (median) household buys a single container of laundry detergent every 4 weeks. This household buys three different brands over the 104 weeks. Since the household-level brand HHI is roughly 0.5, purchases are concentrated at two main brands. However, because preferred brands differ by household, the

TABLE I

SUMMARY STATISTICS OF HOUSEHOLD-LEVEL DATA[a]

	Mean	Median	Std	Min	Max
Demographics					
Income (000's)	35.4	30.0	21.2	<10	>75
Size of household	2.6	2.0	1.4	1	6
Live in suburb	0.53	—	—	0	1
Purchase of laundry detergents					
Price ($)	4.38	3.89	2.17	0.91	16.59
Size (oz.)	80.8	64	37.8	32	256
Quantity	1.07	1	0.29	1.00	4
Duration (days)	43.7	28	47.3	1	300
Number of brands bought over the 2 years	4.1	3	2.7	1	15
Brand HHI	0.53	0.47	0.28	0.10	1.00
Store visits					
Number of stores visited over the 2 years	2.38	2	1.02	1	5
Store HHI	0.77	0.82	0.21	0.27	1.00

[a] For Demographics, Store visits, Number of brands, and Brand HHI, an observation is a household. For all other statistics, an observation is a purchase instance. Brand HHI is the sum of the square of the volume share of the brands bought by each household. Similarly, Store HHI is the sum of the square of the expenditure share spent in each store by each household.

market-level shares are not as concentrated. Finally, the typical household buys mainly at two stores, with most of the purchases concentrated at a single store.

2.2. *The Industry*

Laundry detergents come in two main forms: liquid and powder. Liquid detergents account for 70 percent of the quantity sold. Unlike many other consumer goods, there are a limited number of brands offered. The shares within each segment (i.e., liquid and powder) are presented in the first column of Table II. The top 11 brands account for roughly 90 percent of the quantity sold.

Most brand–size combinations have a regular price. In the sample, the price is at the modal level for 71 percent of the weeks and above it only approximately 5 percent of the time. Defining a sale as any price at least 5 percent below the modal price of each UPC (universal product code) in each store,[2] we find that in our sample 43 and 36 percent of the volume sold of liquid and powder detergent, respectively, was sold during a sale. The median discount during a sale is $0.40, the average is $0.67, the 25th percentile is $0.20, and the

[2] This definition of a sale is not appropriate in cases where the "regular" price shifts due to seasonality or any other reason. This does not seem to be the case in this industry. The definition of a sale matters only for the descriptive analysis in this section. We do not use it in the structural estimation.

TABLE II

BRAND VOLUME SHARES AND FRACTION SOLD ON SALE[a]

	Liquid					Powder				
	Brand	Firm	Share	Cumulative	% on Sale	Brand	Firm	Share	Cumulative	% on Sale
1	Tide	P & G	21.4	21	32.5	Tide	P & G	40	40	25.1
2	All	Unilever	15	36	47.4	Cheer	P & G	14.7	55	9.2
3	Wisk	Unilever	11.5	48	50.2	A & H	C & D	10.5	65	28
4	Solo	P & G	10.1	58	7.2	Dutch	Dial	5.3	70	37.6
5	Purex	Dial	9	67	63.1	Wisk	Unilever	3.7	74	41.2
6	Cheer	P & G	4.6	72	23.6	Oxydol	P & G	3.6	78	59.3
7	A & H	C & D	4.5	76	21.5	Surf	Unilever	3.2	81	11.6
8	Ajax	Colgate	4.4	80	59.4	All	Unilever	2.3	83	
9	Yes	Dow Chemical	4.1	85	33.1	Dreft	P & G	2.2	86	15.2
10	Surf	Unilever	4	89	42.5	Gain	P & G	1.9	87	16.7
11	Era	P & G	3.7	92	40.5	Bold	P & G	1.6	89	1.1
12	Generic	—	0.9	93	0.6	Generic	—	0.7	90	16.6
13	Other	—	0.2	93	0.9	Other	—	0.6	90	19.9

[a]Columns labeled Share are shares of volume (of liquid or powder) sold in our sample, columns labeled Cumulative are the cumulative shares, and columns labeled % on Sale are the percent of the volume, for that brand, sold on sale. A sale is defined as any price at least 5 percent below the modal price, for each UPC in each store. A & H = Arm & Hammer; P & G = Procter and Gamble; C & D = Church and Dwight.

75th percentile is $0.90. In percentage terms, the median discount is 8 percent, the average is 12 percent, and the 25th and 75th percentiles are 4 and 16 percent, respectively. As shown in Table II, there is some variation across brands in the share of the quantity sold on sale.

Detergents come in several sizes. However, about 97 percent of the volume of liquid detergent sold was sold in five different sizes.[3] Sizes of powder detergent are not quite as standardized. Prices are nonlinear in size. The first column in Table III shows the price per 16 oz. unit for several container sizes. Since not all sizes of all brands are sold in all stores, reporting the average price per unit for each size is misleading. Instead, we report the ratio of the size dummy variable to the constant, from a regression of the modal price per 16 ounce regressed on size, brand and store dummy variable.

The data record two types of promotional activities: *feature* and *display*. The *feature* variable measures whether the product was advertised by the retailer (e.g., in a retailer bulletin sent to consumers that week). The *display* variable captures whether the product was displayed differently than usual within the

[3]Toward the end of the sample, ultra detergents were introduced. These detergents are more concentrated and therefore a 100 oz. bottle is equivalent to a 128 oz. bottle of regular detergent. For the purpose of the following numbers we aggregated 128 oz. regular with 100 oz. ultra and 68 oz. regular with 50 oz. ultra.

TABLE III

QUANTITY DISCOUNTS AND SALES[a]

	Quantity Discount (%)	Quantity Sold on Sale (%)	Weeks on Sale (%)	Average Sale Discount (%)	Quantity Share (%)
Liquid					
32 oz.	—	2.6	2.0	11.0	1.6
64 oz.	18.1	27.6	11.5	15.7	30.9
96 oz.	22.5	16.3	7.6	14.4	7.8
128 oz.	22.8	45.6	16.6	18.1	54.7
256 oz.	29.0	20.0	9.3	11.8	1.6
Powder					
32 oz.	—	16.0	7.7	14.5	10.1
64 oz.	10.0	30.5	16.6	12.9	20.3
96 oz.	14.9	17.1	11.5	11.7	14.4
128 oz.	30.0	36.1	20.8	15.1	23.2
256 oz.	48.7	12.9	10.8	10.3	17.3

[a]All cells are based on data from all brands in all stores. The column labeled Discount presents percent quantity discount (per unit) for the larger sizes, after correcting for differences across stores and brands (see text for details). The columns labeled Quantity Sold on Sale, Weeks on Sale, and Average Sale Discount present, respectively, the percent quantity sold on sale, percent of weeks a sale was offered, and average percent discount during a sale, for each size. A sale is defined as any price at least 5 percent below the modal. The column labeled Quantity Share is the share of the total quantity (measured in ounces) sold in each size.

store that week.[4] The correlation between a sale—defined as a price below the modal—and being featured is 0.38. Conditional on being on sale, the probability of being featured is less than 20 percent, while conditional on being featured, the probability of a sale is above 93 percent. The correlation with *display* is even lower, at 0.23, due to the large number of times that the product is displayed but not on sale. Conditional on a display, the probability of a sale is only 50 percent. If we define a sale as the price less than 90 percent of the modal price, both correlations increase slightly, to 0.56 and 0.33, respectively.

2.3. *Preliminary Analysis*

Further descriptive analysis of the data used in this paper can be found in Hendel and Nevo (2006), where we find several patterns consistent with consumer inventory behavior. In line with the marketing findings (summarized above), using the aggregate data we find that duration since previous sale has a positive effect on the aggregate quantity purchased, both during sale and non-sale periods. Both these effects are consistent with an inventory model because the longer is the duration from the previous sale, on average, the lower is the inventory each household currently has, making purchase more likely. Second,

[4]Both these variables have several categories (for example, type of display is end, middle, or front of aisle). We aggregate across these classifications to feature/no feature and display/no display.

we find that indirect measures of storage costs are negatively correlated with households' tendency to buy on sale. Third, both for a given household over time and across households, we find a significant difference between sale and nonsale purchases in both duration from previous purchase and duration to next purchase. To take advantage of the low price, during a sale households buy at higher levels of current inventory. Namely, duration to previous purchase is shorter during a sale. Furthermore, during a sale households buy more and therefore, on average, it takes longer until the next time their inventory crosses the threshold for purchase. Finally, we find that the pattern of sales and purchases during sales across different product categories is consistent with the variation in storage costs across these categories.

3. THE MODEL

3.1. *The Basic Setup*

Consumer h obtains per period utility

$$u(c_{ht}, \nu_{ht}; \boldsymbol{\theta}_h) + \alpha_h m_{ht},$$

where c_{ht} is the quantity consumed of the good in question, ν_{ht} is a shock to utility that changes the marginal utility from consumption, $\boldsymbol{\theta}_h$ is a vector of consumer-specific taste parameters, m_{ht} is the consumption of the outside good, and α_h is the marginal utility from consuming the outside good. The product is offered in J different varieties or brands. The total consumption of all varieties in period t is $c_{ht} = \sum_j c_{jht}$. The stochastic shock ν_{ht} introduces randomness into the consumer's needs, unobserved by the researcher. For simplicity we assume the shock to utility is additive in consumption: $u(c_{ht}, \nu_{ht}; \boldsymbol{\theta}_h) = u(c_{ht} + \nu_{ht}; \boldsymbol{\theta}_h)$. High realizations of ν_{ht} decrease the household's need, decrease demand and make it more elastic. Consumers face random and potentially nonlinear prices.

Consumers in each period decide which brand to buy, how much to buy, and how much to consume.[5] Because the good is storable, quantity not consumed is stored as inventory. As shown in the Appendix, consumption is not affected by which brand is in storage. In the estimation we assume that the purchased amount, denoted by x_{ht}, is simply a choice of size (i.e., consumers choose container size, not how many containers).[6] We denote a purchase of

[5] Instead of making consumption a decision variable, we could assume an exogenous consumption rate, either deterministic or random. Both these alternative assumptions, which are nested within our framework, would simplify the estimation. However, it is important to allow consumption to vary in response to price changes because this is the main alternative explanation to why consumers buy more during sales. Reduced form results in Ailawadi and Neslin (1998), Hendel and Nevo (2006), and Bell and Boztug (2004) report consumption effects for several products.

[6] More than 97 percent of the purchases are for a single unit. In principle, the model could allow for multiple purchases by expanding the choice set to allow for bundles.

brand j and size x by $d_{hjxt} = 1$, where $x = 0$ stands for no purchase, and we assume $\sum_{j,x} d_{hjxt} = 1$. We denote by p_{jxt} the price associated with purchasing x units (or size x) of brand j. The consumer's problem can be represented as

$$(1) \quad V(s_1) = \max_{\{c_h(s_t), d_{hjx}(s_t)\}} \sum_{t=1}^{\infty} \delta^{t-1} E\Bigg[u(c_{ht}, \nu_{ht}; \boldsymbol{\theta}_h) - C_h(i_{h,t+1}; \boldsymbol{\theta}_h) + \sum_j d_{hjxt}(\alpha_h p_{jxt} + \xi_{hjx} + \beta_h a_{jxt} + \varepsilon_{hjxt}) \Bigg| s_1 \Bigg]$$

$$\text{s.t.} \quad 0 \leq i_{ht}, \quad 0 \leq c_{ht}, \quad 0 \leq x_{ht}, \quad \sum_{j,x} d_{hjxt} = 1,$$

$$i_{h,t+1} = i_{ht} + x_{ht} - c_{ht},$$

where s_t denotes the state at time t, $\delta > 0$ is the discount factor, $C_h(i; \theta_h)$ is the cost of storage, ξ_{hjx} is an idiosyncratic taste for brand j that could be a function of brand characteristics or size and varies across consumers, $\beta_h a_{jxt}$ captures the effect of advertising variables on consumer choice, and ε_{hjxt} is a random shock to consumer choice. The latter is size-specific, namely, different sizes get different draws, introducing randomness in the size choice as well. To simplify notation we drop the subscript h in what follows.

At time t, the state s_t consists of the current (or beginning-of-period) inventory i_t, current prices, the shock to utility from consumption ν_t, and the vector of epsilons. In the estimation the parameters in equation (1) are allowed to vary by household. Consumers face two sources of uncertainty in the model: future utility shocks and random future prices. We make the following assumptions about the distribution of these variables.

ASSUMPTION 1: *ν_t is independently distributed over time and across consumers.*

In principle, serial correlation in ν_t can be allowed, but at a significant increase in computational burden.

ASSUMPTION 2: *Prices (and advertising) follow an exogenous first-order Markov process.*

The assumption of a first-order Markov process reduces the state space. It is somewhat problematic because it is hard to come up with a supply model that yields equilibrium prices that follow a first-order process. On the other hand, a first-order process is a reasonable assumption about consumers' memory and formation of expectations. With our assumption a consumer sees the current

prices at the store and forms expectations regarding future prices. A higher order process would require that she recall prices on previous visits. In the application we explore higher order processes, but for now we maintain the first-order assumption.

Assumption 2 implies that the price process is exogenous, namely, conditional on the control variables, the process is independent of the unobserved random components. Given that we use household-level data and can control for many variables, this assumption is reasonable. The main concern might be seasonality or periods of high demand when the likelihood of a sale changes. This is probably not a concern for the product we study herein, but if seasonality is present, it should be modeled into the price process.

ASSUMPTION 3: ε_{jxt} *is independently and identically distributed extreme value type* 1.

This assumption significantly reduces the computational burden. It can be relaxed. We can allow for correlation in the unobserved shocks between brands by assuming that the epsilons are distributed according to some distributions in the generalized extreme value (GEV) class.[7] For simplicity, we present the independently and identically distributed case.

Product differentiation as it appears in equation (1) takes place at the moment of purchase. Taken literally, product differences affect the behavior of the consumer at the store but different brands do not give different utilities at the moment of consumption. This assumption helps reduce the state space. Instead of the whole vector of brand inventories, only the total quantity in stock matters, regardless of brand.

Differentiation at purchase, represented by the ξ_{hjx} term in equation (1), is a way to capture the expected value of the future differences in utility from consumption. The term ξ_{jx} captures the expected utility from the future consumption of the x units of brand j at the time of purchase. This approach is valid as long as (i) brand-specific differences in the utility from consumption enter linearly in the utility function[8] and (ii) discounting is low.[9]

For the brand-specific differences in the utility from consumption to be linear, utility differences from consuming the same quantities of different brands must be independent of the bundle consumed. Thus, we rule out interactions in consumption that arise if, for instance, the marginal utility from consuming Cheerios depends on the consumption of Trix. These interactions between brands are ruled out in standard static discrete choice models.

[7]We have to restrict the distribution to a subset of the GEV family: those with a GEV generating function that is separable across sizes.

[8]Preferences need not be linear. We actually allow for a nonlinear utility from consumption, $u(c)$. Only the brand-specific differences need to enter linearly.

[9]Two issues arise. First, because the timing of consumption is uncertain, the present value of the utility from consumption becomes uncertain ex ante. Second, with discounting, the order in which the different brands already in storage are consumed becomes endogenous.

4. ECONOMETRICS

The structural estimation is based on the nested algorithm proposed by Rust (1987), but has to deal with issues special to our problem. We start by providing a general overview of our estimation procedure and then discuss more technical details.

4.1. *An Overview of the Estimation*

Rust (1987) proposes an algorithm based on nesting the (numerical) solution of the consumer's dynamic programming problem within the parameter search of the estimation. The solution to the dynamic programming problem yields the consumer's deterministic decision rules (in terms of purchases and consumption). However, because we do not observe the random shocks, which are state variables, from our perspective the decision is stochastic. Assuming a distribution for the unobserved shocks, we derive the likelihood of observing each consumer's decision conditional on prices and inventory. We nest this computation of the likelihood into the search for the values of the parameters that maximize the likelihood of the observed sample.

We face two hurdles in implementing the algorithm. First, we do not observe inventory since both initial inventory and consumption decisions are not observed. We deal with the unknown inventories by using the model to derive the optimal consumption in the following way. Assume for a moment that the initial inventory is observed. We can use the procedure described in the previous paragraph to obtain the likelihood of the observed purchases and the optimal consumption levels (which depend on ν), and, therefore, the end-of-period inventory levels. For each inventory level, we can again use the procedure of the previous paragraph to obtain the likelihood of observed purchase in the subsequent period. Repeating this procedure, we obtain the likelihood of observing the whole sequence of purchases for each household. To start this procedure, we need a value for the initial inventory. The standard approach is to use the estimated distribution of inventories to generate the initial distribution. In practice, we do so by starting at an arbitrary initial level and using part of the data (the first few observations) to generate the distribution of inventories implied by the model.

Formally, for a given value of the parameters, the probability of observing a sequence of purchasing decisions, $(d_1, \ldots, d_T)$ as a function of the observed state variables $(p_1, \ldots, p_T)$ is

$$\begin{aligned}(2)\qquad & \Pr(d_1 \cdots d_T | p_1 \cdots p_T) \\ & = \int \prod_{t=1}^{T} \Pr\big(d_t | p_t, i_t(d_{t-1}, \ldots, d_1, \\ & \qquad\qquad \nu_{t-1}, \ldots, \nu_1, i_1), \nu_t\big)\, dF(\nu_1, \ldots, \nu_T)\, dF(i_1).\end{aligned}$$

Note that the beginning-of-period inventory is a function of previous decisions—the previous consumption shocks and the initial inventory. Note also that p_t includes all observed state variables, not just prices, for instance, promotional activities denoted a_t in equation (1). The probability inside the integral on the right-hand side of equation (2) represents integration over the set of epsilons that induce d_t as the optimal choice and is given by

$$\text{(3)} \qquad \Pr(d_{jx}|p_t, i_t, \nu_t) = \frac{\exp(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + M(s_t, j, x))}{\sum_{k,y} \exp(\alpha p_{kyt} + \xi_{ky} + \beta a_{kyt} + M(s_t, k, y))},$$

where $M(s_t, j, x) = \text{Max}_c\{u(c+\nu_t) - C(i_{t+1}) + \delta E(V(s_{t+1})|d_{jx}, c, s_t)\}$ and $E(V)$ is the expectation of the future V as a function of today's state and actions. Note that the summation in the denominator is over all brands and all sizes.

The second problem is the dimensionality of the state space. Households in our sample buy several brand–size combinations, which are offered at many different prices. The state space includes not only the individual-specific inventory and shocks, but also the prices of all brands in all sizes and their promotional activities. The state space and the transitions probabilities across states, in full generality, make the standard approach computationally infeasible.

We therefore propose the following three-step procedure. The first step consists of maximizing the likelihood of observed brand choice *conditional* on the size (quantity) bought in order to recover the marginal utility of income α and the parameters that measure the effect of advertising, β and ξ. As we show below, we do not need to solve the dynamic programming problem to compute this probability. We estimate a static discrete choice model, restricting the choice set to options of the same size (quantity) actually bought in each period. This estimation yields consistent, but potentially inefficient, estimates of these parameters. In the second step, using the estimates from the first stage, we compute the *inclusive values* associated with each size (quantity) and their transition probabilities from period to period. Finally, we apply the nested algorithm to the simplified dynamic problem. We estimate the remaining parameters by maximizing the likelihood of the observed sequence of sizes (quantities) purchased. The simplified problem involves quantity choices exclusively. Rather than have the state space include prices of all available brand–size combinations, it includes only a single "price" (or inclusive value) for each size.

Intuitively, the time independent nature of the shocks enables the decomposition of the likelihood of the individual choices into two components that can be separately estimated. First, at any specific point in time, when the consumer purchases a product of size x, we can estimate her preferences for different brands. Second, we can estimate the parameters that determine the dynamic

(storing) behavior of the consumer by looking at a simplified version of the problem, which treats each size as a single choice.[10]

4.2. *The Three-Step Procedure*

We now show that the breakup of the likelihood follows from the primitives of the model.

STEP 1—Estimation of the "Static" Parameters: To simplify the computation of the likelihood, note that the probability of choosing brand j and size x can be written as

$$\Pr(d_{jt}=1, x_t|p_t, i_t, \nu_t) = \Pr(d_{jt}=1|p_t, x_t, i_t, \nu_t)\Pr(x_t|p_t, i_t, \nu_t).$$

In general, this does not help because we need to solve the consumer's dynamic programming problem to be able to compute $\Pr(d_{jt}=1|p_t, x_t, i_t, \nu_t)$. However, given the preceding model and assumptions, we can compute this conditional probability without solving the dynamic programming problem. We rely on two results. The optimal consumption, conditional on the quantity purchased, is not brand-specific (see Lemma 1 in the Appendix). Thus, the term $M(s_t, j, x)$ is independent of brand choice. This in itself is not enough to deliver the result because the conditional distribution of epsilon might be a function of x. If indeed the actual choice (given the observed state, i.e., prices) conveyed information about the distribution of the epsilons, we would have to fully solve the model to figure out the conditional distribution of the error (more details in Section 4.3.2). Assumption 3 implies that, after the appropriate cancellations,

$$\begin{aligned}(4)\qquad \Pr(d_{jt}=1|x_t, i_t, p_t, \nu_t) &= \frac{\exp(\alpha p_{jxt}+\xi_{kx}+\beta a_{kxt})}{\sum_k \exp(\alpha p_{kxt}+\xi_{kx}+\beta a_{kxt})}\\ &= \Pr(d_{jt}=1|x_t, p_t),\end{aligned}$$

where the summation is over all brands available in size x_t at time t.

Thus, our approach is to estimate the parameters that affect brand choice (i.e., marginal utility of income, the vector of parameters β, and brand-specific and potentially household-specific fixed effects) by maximizing the product, over time and households, of $\Pr(d_{jt}=1|p_t, x_t)$. This amounts to estimating a

[10]We are aware of two instances in the literature that use similar ideas. First, one way to estimate a static nested logit model is first to estimate the choice within a nest, compute the inclusive value, and then to estimate the choice among nests using the inclusive values (Train (1986)). Second, in a dynamic context a similar idea was proposed by Melnikov (2001). In his model (of purchase of durable products) the value of all future options enters the current no-purchase utility. He summarizes this value by the inclusive value.

static brand choice model where the choice set includes only brands offered in the same size as the actual purchase.

STEP 2—Inclusive Values: To compute the likelihood of a sequence of purchased quantities, we show in the next section that we can simplify the state space of the dynamic programming problem. The state variables of the simplified problem are the inclusive values of each size (quantity), which can be thought of as a quality adjusted price index for all brands of size x. They are given by

$$\omega_{xt} = \log\left\{\sum_k \exp(\alpha p_{kxt} + \xi_{kx} + \beta a_{kxt})\right\}. \tag{5}$$

All the information needed to compute the inclusive values and their transition probabilities from period to period is contained in the first stage estimates.

We show below that the dynamic problem can be rewritten in terms of inclusive values, so that the state space collapses to a single index per size. For this to work, we make the following assumption:

ASSUMPTION 4: *$F(\omega_t|s_{t-1})$ can be summarized by $F(\omega_t|\omega_{t-1})$.*

Instead of keeping track of the prices of ten brands times four sizes (roughly the dimensions in our data), we have to follow only four quality adjusted prices. If the marginal utility from income and the brand preferences are household-specific, then the inclusive values and their future distribution $F(\omega_t|\omega_{t-1})$ will be household-specific. A household-specific process requires that we solve the dynamic program separately for each household. In the application, we group households into six types, letting the process vary by type.

The main loss when the process is defined this way is that transition probabilities are exclusively a function of the inclusive values. Two price vectors that yield the same vector of inclusive values will have the same transition probabilities to next period's state. This restriction is testable and to some extent can be relaxed. In the regression of current on previous inclusive values, we can add vectors of previous prices. Under our assumption, previous prices should not matter independently once we control for the vector of current inclusive values. A full fix is to allow the distribution of the inclusive values to depend on the whole vector of current prices. This would naturally undo part of the computational advantage of the inclusive values.[11]

[11] If we assume that the inclusive values depend on the whole vector of prices the third stage becomes more computationally demanding, but the split remains valid.

STEP 3—The Simplified Dynamic Problem: In the third step we estimate the remaining dynamic parameters by maximizing the likelihood of purchases implied by the simplified problem. In the simplified problem, the consumer chooses whether and what quantity to purchase. Her flow utility of purchasing quantity x is given by $\omega_{xt} + \varepsilon_{xt}$. The inclusive value ω_{xt} is the utility expected by the consumer from all brands of size x in the original problem before knowing the realizations of ε_{jxt} (McFadden (1981)). The consumer in the simplified problem observes only a summary of the state variables (given by the inclusive values) and decides what quantity to purchase. The Bellman equation associated with the simpler problem is

$$\begin{aligned} &V(i_t, \omega_t, \varepsilon_t, \nu_t) \\ &\quad = \underset{\{c,x\}}{\operatorname{Max}}\{u(c+\nu_t) - C(i_{t+1}) + \omega_{xt} + \varepsilon_{xt} \\ &\qquad\qquad + \delta E[V(i_{t+1}, \omega_{t+1}, \varepsilon_{t+1}, \nu_{t+1}) | i_t, \omega_t, \varepsilon_t, \nu_t, c, x]\}. \end{aligned}$$

Using the estimated inclusive values and the transition probabilities, we estimate the utility and the storage cost functions by applying the nested algorithm to compute the likelihood of purchasing a size (quantity). The following claim shows the equivalence of the likelihood computed from the original problem and that computed from the simplified one, thus establishing the validity of using the simpler problem for estimation.

CLAIM 1: $\Pr(x_t | i_t, p_t, \nu_t) = \Pr(x_t | i_t, \omega(p_t), \nu_t)$, *where the left-hand side is the probability of choosing* x (*summing over brand choices*) *in the original problem defined in equation* (3), *and the right-hand side is the probability of choosing* x *in the simplified problem*.

There are two steps to prove this claim (see the Appendix). The first step is to note that the solutions to the original and the simplified problems are characterized by the same $E(V)$. The original problem is characterized by the Bellman equation

$$\begin{aligned} V(s_t) = \underset{\{c,d_{jx}\}}{\operatorname{Max}}\bigg\{ &u(c+\nu_t) - C(i_{t+1}) + \sum_{j,x} d_{jx}(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + \varepsilon_{jxt}) \\ &+ \delta E[V(s_{t+1}) | s_t, c, d_{jx}]\bigg\}. \end{aligned}$$

The equivalence is not obvious, because in one case the consumer observes the whole state, s_t, when she decides what to purchase, whereas in the other case she picks a quantity x after having observed only the expected utility from that quantity, namely ω_{xt}. The key to the equivalence is in Assumption 3, which allows us to obtain a summary of the expected utility from all products of a

particular size, and in Assumption 4, which enables us to write the transition probabilities as a function of the inclusive values exclusively.

The second step of the proof shows the equivalence of the probability of choosing size x in the original problem, defined by summing over the brand choice probabilities given in equation (3), and the choice probability implied by the simplified model, where size x is a single choice evaluated at the inclusive value generated by the vector p_t. This follows almost directly from the definition of the inclusive values (and Assumption 3).

Despite the reduction in the number of state variables, the value function of the simpler problem is still computationally burdensome to solve. To solve it we use value function approximation with policy function iteration. We closely follow Benitez-Silva, Hall, Hitsch, Pauletto, and Rust (2000), where further details can be found. Briefly, the algorithm consists of iterating the alternating steps of policy evaluation and policy improvement. The value function is approximated by a polynomial function of the state variables. The procedure starts with a guess of the optimal policy at a finite set of points in the state space. Given this guess, and substituting the approximation for both the value function and the expected future value, one can solve for the coefficients of the polynomial that minimize the distance (in a least squares sense) between the two sides of the Bellman equation. Next the guess of the policy is updated. This is done by finding, for every state, the action that maximizes the sum of current return and the expected discounted value of the value function. The expected value is computed using the coefficients found in the first step and the expected value of the state variables. We perform this step analytically. These two steps are iterated until convergence (of the coefficients of the approximating function). The output of the procedure is an approximating function that can be used to evaluate the value function (and the expected value function) at any point in the state space. See Bertsekas and Tsitsiklis (1996) and Benitez-Silva et al. (2000) for more details on this procedure, as well as its convergence properties.

4.3. *Identification, Heterogeneity, and Alternative Methods*

4.3.1. *Identification*

We informally discuss identification. The identification of the static parameters is standard. Variation over time in prices and advertising identify the household's sensitivity to price and to promotional activities, denoted by α and β. As we pointed out in Section 2.2, sales are not perfectly correlated with feature and display activity, and therefore the effects can be separately identified. Brand and size effects are identified in the first stage from variations in shares across products. Household heterogeneity in the static parameters is captured by making the sensitivity to promotional activities, brand effects, and size effects functions of household demographics, as well as allowing for household-specific brand effects.

The identification of the dynamic parameters is more subtle. The third stage involves the estimation of the utility and storage cost parameters that maximize the likelihood of the observed sequence of quantities purchased (container sizes) over the sample period. If inventory and consumption were observed, then identification would follow the standard arguments (see Rust (1996), Magnac and Thesmar (2002), and Aquirregabiria (2005)). However, we do not observe inventory or consumption, so the question is what feature of the data allows us to identify functions of these variables?

The data tell us about the probability of purchase conditional on current prices (i.e., the current inclusive values) and past purchases (amounts purchased and duration from previous purchases). Suppose that we see that this probability is not a function of past behavior. Then we would conclude that consumers are purchasing for immediate consumption and not for inventory. On the other hand, if we observe that the purchase probability is a function of past behavior and we assume that preferences are stationary, then we conclude that there is dynamic behavior. Regarding storage costs, consider the following example. Suppose we observe two consumers who face the same price process purchase the same amount over a given period. However, one of them purchases more frequently than the other. This variation will lead us to conclude that this consumer has higher storage costs.

More generally, given the process of the inclusive values, preferences and storage costs determine consumer behavior. For a given storage cost function, preferences determine the level of demand. In contrast, given preferences, different storage cost levels determine interpurchase duration and the extent to which consumers can exploit price reductions. Higher storage costs reduce consumers' benefit from sales and shorten the average duration between purchases. In the extreme case of no storage (or very high storage cost), interpurchase duration depends exclusively on current prices, because the probability of current purchase is independent of past purchases. This suggests a simple way to test the relevance of the inventory model, based on the impact of previous purchases on current behavior. Preferences and storage costs are recovered from the relationship between purchases, prices, and previous purchases. We have no reason to believe that costs and preferences are identified nonparametrically or even that flexible functional forms can be estimated.

The split between the quantity purchased and brand choice provides some insight into the determinants of demand elasticities. There are two sets of parameters that determine price responses. The static parameters recovered in stage one determine the substitutability across brands, while the utility and inventory cost parameters recovered in stage three determine the responsiveness to prices in the quantity dimension. Both sets of estimates are needed to simulate the responses to price changes.

The split provides both an intuitive interpretation of the determinants of substitution patterns as well as a shortcut to separate long-run from short-run

price responses. The basic insight is that in order to purge elasticities from timing effects—as a first approximation—one can estimate demand at the individual level, conditional on the size of the purchase. This approximation might prove helpful when the full model is too complicated to estimate or the data are insufficient.

4.3.2. *Heterogeneity in brand preferences*

Three assumptions are critical to justify the split in the likelihood. We already discussed the implications and limitations of the first two—product differentiation is modeled as taking place at the time of purchase and Assumption 4. Also critical for the analysis is the assumption that the error terms ε_{jxt} are identically and independently distributed type I extreme value, both across choices and over time. As we mentioned, we can relax the independence across brands by allowing for a GEV distribution. Here we discuss ways to allow for persistent heterogeneity.

Our procedure allows for heterogeneity in brand preferences that is a function of observed household attributes and observed past behavior. However, we cannot allow for a persistent random component. One can see from equation (3) why the unobservable brand–size preferences must be uncorrelated over time. Suppose there are different (unobservable) types in the population that differ in their brand preferences or in their sensitivity to price and advertising. To compute the choice probabilities (unconditional on type), we have to integrate over the distribution of these types. The probability of brand choice conditional on size purchased and *conditional* on the type (of consumer) will still be independent of the various dynamic components. The problem, however, is that in order to compute the brand choice probability conditional on size (but unconditional on type) we have to integrate over the distribution of types *conditional* on the size purchased. Figuring out this distribution requires essentially solving the dynamic problem.

The main consequence of not having persistent preference shocks is that we cannot allow for random effects in the first stage of the estimation. Notice that unobserved heterogeneity can be introduced in the dynamic part of the model; indeed because of its computational simplicity, this can be done in a relatively general way. Random effects usually enter choice models in the brand preferences and in the marginal impact of price and other variables. Heterogeneity along these dimensions might generate interesting dynamics. For instance, consider the case of heterogeneity in brand preferences. A consumer with a high unobserved shock preference for Tide is likely not to react to deals on other brands and waits for deals on Tide if the shock is persistent. If her inventories are running low, she may prefer to purchase a small container of an alternative brand as she waits for Tide to go on sale.

Instead of random effects, we can allow for heterogeneity by including observed household heterogeneity, classifying the households into types, allowing for differences in the choice based on past behavior, and allowing for

household-brand-specific fixed effects. Because the household-brand dummy variables are estimated in a static conditional logit, they do not substantially increase the computational cost.[12] Notice that we need only to estimate preferences for the brands actually purchased by each household. For brands that a household never bought in the sample (which are the majority), we just eliminate them from the household choice set. Absence from the choice set is equivalent to a sufficiently negative brand dummy. Clearly, we do not know if the household would buy this brand at prices outside those observed in the sample range, but that is a data limitation: the data do not inform us about out-of-sample prices anyway.

4.3.3. *Alternative methods*

The estimation of the full model without the assumptions that enable the split (of the likelihood) would not be tractable for most products that come in several sizes and brands. The dynamic problem would have an extremely large state, which includes the inventories of all brands held by the household as well as the price vector of all brands in all sizes, in addition to other promotional activities for each product–size combination.

Erdem, Imai, and Keane (2003) propose a different approach. Their solution to reduce the complexity of the problem is to assume that once the quantity to be consumed is determined, each brand in storage is consumed. Moreover, the consumption share of each brand is proportional to the share of that brand in storage. In other words, if the storage is made of 40% of one brand and 60% of the other, then consumption will be made up of both brands in those proportions. This, together with the assumption that brand differences in quality enter linearly in the utility function, implies that only the total inventory and a quality weighted inventory matter as state variables. To reduce the dimensionality of the price vector, they estimate only the price process of the dominant container size and assume that price differentials per ounce with other containers is independently and identically distributed. This simplifies the states and transitions from current to future prices, because only the prices of the dominant size are relevant state variables. Finally, to further simplify the state space, they ignore other promotional activities.

4.4. *Computing Standard Errors*

The standard errors computed in the third step of the estimation have to be adjusted because the inclusive values and the transition parameters were

[12]The estimation of fixed effects is, in principle, problematic in nonlinear models. There are basically two ways around this. First, extend the conditional logit approach (Chamberlain (1983)) to deal with household-brand fixed effects. Second, estimate the parameters using maximum likelihood. Because in our case T is large, assuming it grows asymptotically is not unreasonable, in which case the standard incidental parameters problem is not an issue. The estimation of hundreds of household-specific brand fixed effects is feasible because the likelihood function of conditional logit is well behaved.

estimated in the first and second steps. This can be done using the correction methods proposed by Murphy and Topel (1985). The key in this approach is to compute the derivative of the third step likelihood with respect to the parameters estimated in the first and second steps. These derivatives can be evaluated numerically: we perturb each parameter slightly, resolve the dynamic programming problem, and see the impact on the likelihood. This computation is simplified significantly because the derivatives with respect to the first stage parameters can be written as the derivatives of the likelihood with respect to the inclusive value times the derivative of the inclusive value with respect to the parameter. The latter is easy to compute analytically, which significantly reduces the number of perturbations required of the third step. In the results below the correction increased the standard errors by less than 10 percent for most parameters.

5. RESULTS

To estimate the model, we have to choose functional forms. We assume $u(c_t + \nu_t) = \gamma \log(c_t + \nu_t)$, $C(i_t) = \beta_1 i_t + \beta_2 i_t^2$, and ν_t is distributed log normal. For the evolution in the inclusive values, we assume that ω_{st} is distributed normal with mean $\gamma_{s0} + \gamma_{s1}\omega_{1,t-1} + \cdots + \gamma_{s4}\omega_{4,t-1}$ and standard deviation σ_s for $s = 1, \ldots, 4$, where the actual size is 32 oz. times s. We explore below adding more lags, the normality assumption, and letting the process vary by household type. The dynamic programming problem was solved by parametric policy approximation. The approximation basis used is a polynomial in the natural logarithm of inventory and levels of the other state variables. We will describe various ways in which we tested the robustness of the results. The estimation was performed using a sample of 218 households. The households were selected based on the following criteria: (i) they made more than 10 purchases of detergents, (ii) but no more than 50 purchases, and (iii) at least 75 percent of their purchases of detergents were of liquid detergent.[13] The households in the sample visit a supermarket 45–103 times. These households made 3,772 purchases of liquid detergents. The third stage is estimated using visits 11–35 of each household. The first 10 visits are used to generate the distribution of initial inventories. The late visits are eliminated to avoid right censoring in a uniform way. In what follows, we limit the analysis to liquid detergent. This product is easier to handle, more concentrated, and offered in fewer container sizes.

[13]Only a couple of household were eliminated because they purchased more than 50 times. We dropped these households because their purchases were so frequent—in one case essentially every week and multiple units each time—that we did not think our model applied to them. The number of households that purchased less than 10 times is more numerous, but of little impact on the elasticities (as they amount to a small share of total sales). We think it is safer to keep them out of the sample because they are candidates to purchase detergent in alternative stores.

5.1. *Parameter Estimates*

The parameter estimates are presented in Tables IV–VI. Table IV presents the estimates from the first stage, which is a (static) conditional logit brand choice conditional on size. This stage was estimated using choices by all households in the sample, where the choice set was restricted to products of the same size as the observed purchase. We introduce heterogeneity in three ways. First, we interact price with observable household characteristics. Second, we allow for household–brand specific effects. This is doable in our sample because each household purchases a small number of brands and we have a relatively long time series. Third, we eliminate from the household choice set brands not purchased over the whole sample period by that household. This reduces the number of choices significantly because most households purchase a small number of brands (the median household purchases three brands; see Table I).

The different columns in Table IV present specifications that vary in the variables included. We conclude three things from this table. First, we note the effect of including feature and display on the price coefficient, which can be seen by comparing columns (ii) and (iii) (as well as (ix) and (x)). Once feature and display are included, the price coefficient is roughly cut by half, which implies that the price elasticities are roughly 50 percent smaller.[14] The size of the change is intuitive. It implies that the large effect on quantity sold seemingly associated with price changes is largely driven by the feature and display promotional activity. This suggests that one has to be careful when interpreting estimates that do not properly control for promotional activities other than sales.[15]

More importantly these effects highlight one of the advantages of our approach: we can easily control for various observed variables. An alternative approach proposed by Erdem, Imai, and Keane (2003) can, in principle, incorporate promotional activities, but due to the computational cost they do not do so in practice.

Second, we see the impact of heterogeneity in columns (iv)–(x), where we interact price with three demographic variables: dummy variables that equal one if the family lives in the suburban market, if the family is nonwhite, and if the family has more than four people. These interactions are highly significant. The signs on the coefficients make sense. Larger families, nonwhite people (who in our sample have lower income), and suburban shoppers are more price sensitive.

[14]This finding is not new to our paper and has been pointed out before in the marketing literature.

[15]The problem here is of price endogeneity. Prices are (negatively) correlated with promotional activities. If one does not control for promotional activity the price coefficient will be biased. Our control is relatively rough and in principle might not fully control for the full impact of promotional activity.

TABLE IV

FIRST STEP: BRAND CHOICE CONDITIONAL ON SIZE[a]

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Price	−0.51	−1.06	−0.49	−0.26	−0.27	−0.38	−0.38	−0.57	−1.41	−0.75
	(0.022)	(0.038)	(0.043)	(0.050)	(0.052)	(0.055)	(0.056)	(0.085)	(0.092)	(0.098)
*Suburban dummy				−0.33	−0.30	−0.34	−0.33	−0.25	−0.45	−0.19
				(0.055)	(0.061)	(0.055)	(0.056)	(0.113)	(0.127)	(0.127)
*Nonwhite dummy				−0.34	−0.39	−0.38	−0.33	−0.34	−0.33	−0.26
				(0.075)	(0.083)	(0.076)	(0.076)	(0.152)	(0.166)	(0.168)
Large family				−0.23	−0.13	−0.21	−0.22	−0.46	−0.38	−0.43
				(0.080)	(0.107)	(0.080)	(0.082)	(0.181)	(0.192)	(0.195)
Feature			1.06	1.05	1.08	0.92	0.93	1.08		1.05
			(0.095)	(0.096)	(0.097)	(0.099)	(0.100)	(0.123)		(0.126)
Display			1.19	1.17	1.20	1.14	1.15	1.55		1.52
			(0.069)	(0.070)	(0.071)	(0.071)	(0.072)	(0.093)		(0.093)
Brand dummy variable		✓	✓	✓	✓					
*Demographics					✓					
*Size						✓				
Brand–size dummy variable							✓			
Brand-HH dummy variable								✓		
*Size									✓	✓

[a]Estimates of a conditional logit model. An observation is a purchase instance by a household. Options include only products of the same size as the product actually purchased. Asymptotic standard errors are shown in parentheses.

To allow for heterogeneity in brand preferences, we interact the brand dummy variables with the demographic variables in column (v). Together the demographics variables generate eight different "types" of households. In columns (viii)–(x) we allow for household–brand specific effects. This is the richest time invariant form of heterogeneity in brand preference possible in these data.

Third, we see the importance of allowing brand preferences to vary by size in columns (vi), (vii), (ix), and (x), where we interact the brand–dummy variables with size (either by multiplying the dummy by the size (in columns (vi), (ix), and (x)) or by allowing a full interaction). Notice that interacting brand effects with sizes makes the preference for each specific product proportional to the container size purchased. Namely, if a consumer prefers Tide, then it is reasonable to increase or rescale her preference by the size of the container she is purchasing.

Table V reports the estimates of the price process. This process was estimated using the inclusive values (given in equation (5)) computed from the estimates of column (x) in Table IV. The inclusive values can be considered a quality weighted price: for each household, all the different prices (and promotional activities) of all the products offered in each size are combined into

TABLE V

SECOND STEP: ESTIMATES OF THE PRICE PROCESS[a]

	Same Process for All Types				Different Process for Each Type			
	ω_{2t}	ω_{4t}	ω_{2t}	ω_{4t}	ω_{2t}	ω_{4t}	ω_{2t}	ω_{4t}
$\omega_{1,t-1}$	0.003	−0.014	0.005	0.014	−0.023	−0.005	−0.019	0.007
	(0.012)	(0.011)	(0.014)	(0.014)	(0.017)	(0.014)	(0.019)	(0.015)
$\omega_{2,t-1}$	0.413	0.033	0.295	0.025	0.575	−0.003	0.520	0.011
	(0.007)	(0.010)	(0.008)	(0.007)	(0.013)	(0.010)	(0.016)	(0.013)
$\omega_{3,t-1}$	0.003	−0.034	0.041	−0.006	0.027	−0.072	0.051	−0.018
	(0.007)	(0.007)	(0.009)	(0.009)	(0.020)	(0.016)	(0.025)	(0.020)
$\omega_{4,t-1}$	0.029	0.249	0.026	0.236	−0.018	0.336	−0.018	0.274
	(0.008)	(0.008)	(0.008)	(0.017)	(0.020)	(0.016)	(0.021)	(0.017)
$\sum_{\tau=2}^{5} \omega_{1,t-\tau}$			−0.003	−0.012			−0.008	−0.003
			(0.005)	(0.004)			(0.006)	(0.005)
$\sum_{\tau=2}^{5} \omega_{2,t-\tau}$			0.089	0.006			0.073	−0.004
			(0.003)	(0.002)			(0.005)	(0.004)
$\sum_{\tau=2}^{5} \omega_{3,t-\tau}$			−0.008	−0.009			−0.004	−0.016
			(0.003)	(0.003)			(0.008)	(0.006)
$\sum_{\tau=2}^{5} \omega_{4,t-\tau}$			−0.013	0.018			−0.008	0.056
			(0.003)	(0.003)			(0.007)	(0.005)

[a]Each column represents the regression of the inclusive value for a size (32, 64, 96, and 128 ounces, respectively) on lagged values of all sizes. The inclusive values were computed using the results in column (x) of Table IV. The four left columns impose the same process for each household type; the four right columns allow for a different process for each type. Reported results are only for households of type 3, that is, households in market 1 with large families. Results for other types are available from the authors.

a single index. This index varies by household, because the brand preferences are allowed to vary.

The inclusive value is a summary of all the variables that impact utility, in particular prices and advertising. In our model, the consumer realizes that advertising will impact her future choice and therefore she forms expectations regarding future advertising. It may seem awkward that expected advertising affects current behavior. Alternatively, we could assume that advertising does not have dynamic implications, i.e., we could compute an inclusive value without advertising. In such a case, the consumer is repeatedly surprised by the effect of advertising (namely, advertising affects the choice probability without the consumer foreseeing it will happen). Such specification implies an inconsistency between the consumers' expected and actual probability of purchase. We opted for the internally consistent version of advertising.

The first four columns of Table V display the estimated parameters for the two main sizes (64 and 128 oz.), restricting the process to be the same for all households. The last four columns allow a different process for different household types. The results are presented for households in the urban market with large families (type 3). Within each set, the first two columns display results for a first-order Markov process. The point estimates suggest that the lagged value of own size is the most important in predicting future prices. Letting the price process vary by household type changes the parameters of the price process, but seems to have little impact on the bottom line (the results displayed below). In principle, one could allow the process to differ by household, but that would mean solving a different dynamic problem for each individual. Given the shortcut, this might be feasible, but it would significantly increase the computational burden. Given the small impact on the final results in going from one process to six, we decided against this option.

Considering the supply side, there are good reasons to believe that prices will not follow a first-order process. To explore alternatives to the first-order Markov assumption, in the next set of columns we include the sum of five additional lags. We also estimated, but do not display, a specification that allows these five lags to enter with separate coefficients. These additional lags do not significantly improve the fit. Therefore, we stick to a first-order Markov process.

Finally, assuming the inclusive values are distributed normally might seem strange given that the product-specific prices tend to be at a modal nonsale price with occasional reductions. The inclusive values aggregate across several prices with such patterns and also promotional activity. Although the resulting variable is distributed in a bell-like shape, a formal test rejects the hypothesis that the inclusive values are distributed normal. In principle, this assumption can be relaxed, at a substantial computational cost.

Table VI reports third stage estimates. We allow for six different types of households that vary by market and family size. Each type is allowed different utility and storage cost parameters. We also include size fixed effects that are

TABLE VI

THIRD STEP: ESTIMATES OF DYNAMIC PARAMETERS[a]

Household Type:	1	2	3	4	5	6
	Urban Market			Suburban Market		
Household Size:	1–2	3–4	5+	1–2	3–4	5+
Cost of inventory						
Linear	9.24	6.49	21.96	4.24	4.13	11.75
	(0.01)	(0.02)	(0.09)	(0.01)	(0.17)	(5.3)
Quadratic	−3.82	1.80	−35.86	−8.20	−6.14	−0.73
	(29.8)	(1.77)	(0.19)	(0.03)	(1.69)	(1.53)
Utility from consumption	1.31	0.75	0.51	0.08	0.92	3.80
	(0.02)	(0.09)	(0.21)	(0.03)	(0.18)	(0.38)
Log likelihood	365.6	926.8	1,530.1	1,037.1	543.6	1,086.1

[a]Asymptotic standard errors are shown in parentheses. Also included are size fixed effects, which are allowed to vary by household type.

allowed to vary by type (not reported in the table). Most of the parameters are statistically significant at standard significance levels. Households that live in the suburban market (where houses are on average larger) have lower storage costs.

To get an idea of the economic magnitude, consider the following. If the beginning-of-period inventory is 30 oz. (the median reported below), then buying a 128 oz. bottle increases the storage cost, relative to buying a 64 oz. bottle, by roughly \$0.20–0.75, depending on the household type. As we can see from Table III, the typical savings from nonlinear pricing are roughly \$0.40, which implies that the high storage cost types would not benefit from buying the larger size, whereas the low storage cost types would.

For this sample the estimated median inventory held is 27–33 oz., depending on the type. There is more variation across the types at the higher end of the distribution. The mean weekly consumption is between 22 and 36 oz., for different types (with the 10th and 90th percentiles varying between 4 and 6, and 85 and 115, respectively). If we assume that the households had constant consumption equal to their total purchases divided by the number of weeks, we get very similar average consumption. Furthermore, we can create an inventory series by using the assumption of constant consumption and observed purchases. If we set the initial inventory for such a series so that the inventory will be nonnegative, then the mean inventory is essentially the same as the inventory simulated from the model.

5.2. *Fit and Robustness*

Ideally, to further test the fit of the model, we would compare the simulated consumption (and inventory) behavior to observed data. However, consumption and inventory are not observed. We focus instead on the model's

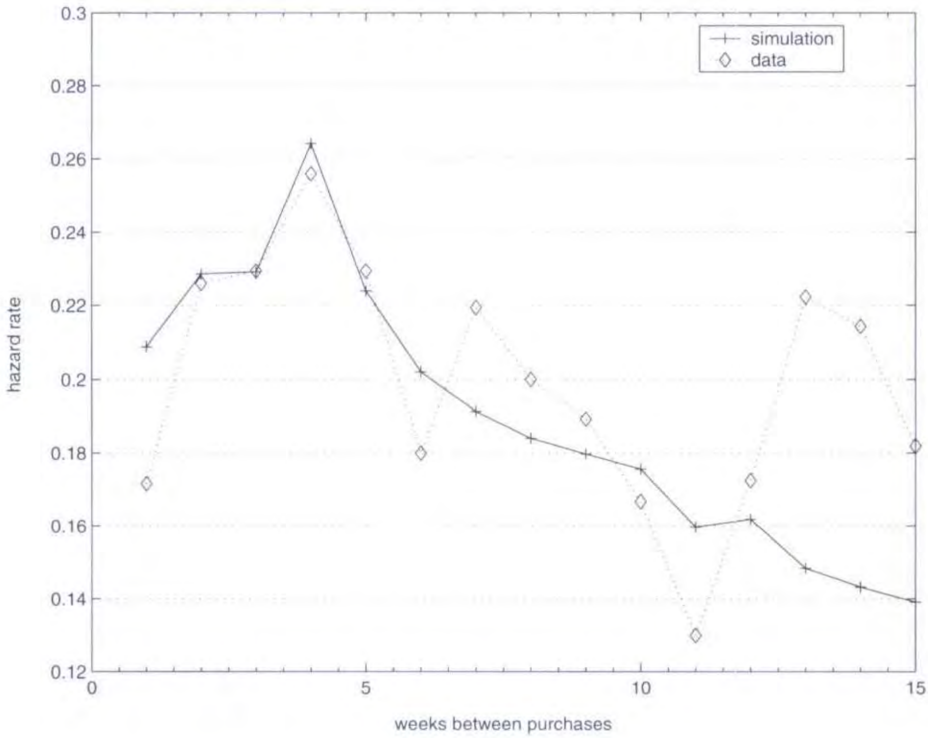

FIGURE 1.—Hazard rate of purchases.

prediction of interpurchase duration. Figure 1 displays the hazard rate of purchasing by duration week from last purchase. The hazard rate in this case is the probability that you purchase if you have not purchased up to now. If the probability of purchase is not duration dependent, than the hazard rate would be constant and equal to roughly 0.25 in our data. The data display a clear pattern: the probability of purchase gradually increases until week 4 and then gradually declines. The simulation from the model traces this pattern reasonably well. The predicted purchase probability one week after a purchase is higher than observed in the data. The model does a better job fitting the subsequent weeks—clearly better than a static model.

We tested the robustness of the results in several ways. First, we explored a variety of methods to solve the dynamic programming problem. In addition to the approximation method we used to generate the final set of results, we explored dividing the state space into a discrete grid. We then solved the dynamic programming problem over this grid and explored two ways to take this solution to the data. We divided the data into the same discrete grid and used the exact solution. We also used the exact solution on the grid to fit continuous value and policy functions, and used these to evaluate the data. We also ex-

plored a variety of functional forms for both the utility from consumption and the cost of inventory.

The estimated parameters did vary across several of these robustness tests. Indeed, even in our preferred specification the likelihood was relatively flat, which suggests that some of the identification issues we discussed are relevant in this data set. However, in the cases we examined, the implications discussed next were robust.

5.3. *Implications*

In this section we present the implications of the estimates, and compare them to static ones. In Table VII we present own- and cross-price long-run elasticities simulated from the dynamic model. The elasticities were simulated as follows. Using the observed prices, we simulated choice probabilities. We then generated the increased prices by adding a small amount to the observed price paths of each of the different products (brand and size). To evaluate long-run price responses, we generated permanent changes in the process (i.e., a change in the whole path of prices, not just the current price). We then reestimated the price process (although in practice the prices changes were small enough that the change in the price process was negligible) and solved for the optimal behavior given the new price process. Finally, we simulated new choice probabilities, used them to compute the change in choice probabilities relative to the initial values, and computed the price elasticities.

The results are presented in Table VII. Cell entries i and j, where i indexes row and j indexes column, present the percent change in market share of brand i with a 1 percent change in the price of j. All columns are for a size of 128 oz., the most popular size. The own-price elasticities are between -2.5 and -4.5. The cross-price elasticities also seem reasonable.[16] There are several patterns worth pointing out. First, cross-price elasticities to other brands of the same size, 128 oz., are generally higher. This is driven by the type-specific size fixed effects. Therefore, if the price of a product changes, consumers currently purchasing it are more likely to substitute toward similar size containers of a different brand.

Second, the cross-price elasticities to other sizes of the same brand are generally higher, sometimes over 20 times higher, than the cross-price elasticities to other brands. This suggests that these brands have a relatively loyal base. This pattern is driven by the heterogeneity estimated in the first step.

Third, the cross-price elasticities to the outside option, i.e., no purchase, are generally low. This is quite reasonable because we are looking at long-run responses, which reflect purely a consumption effect, presumably small for detergents. The substitution from say 128 oz. Tide to the outside option represents

[16]At first glance the cross-price elasticities might seem low. However, there is a large number of products: different brands in different sizes. If we were to look at cross-price elasticities across brands (regardless of the size), the numbers would be higher, roughly four times higher.

TABLE VII

LONG-RUN OWN- AND CROSS-PRICE ELASTICITIES[a]

Brand	Size (oz.)	All[b]	Wisk	Surf	Cheer	Tide	Private Label
All[b]	32	0.418	0.129	0.041	0.053	0.131	0.000
	64	0.482	0.093	0.052	0.033	0.085	0.006
	96	0.725	0.092	0.036	0.035	0.100	0.002
	128	−2.536	0.154	0.088	0.059	0.115	0.007
Wisk	32	0.088	0.702	0.046	0.012	0.143	0.006
	64	0.078	0.620	0.045	0.014	0.116	0.004
	96	0.066	0.725	0.051	0.022	0.135	0.009
	128	0.126	−2.916	0.083	0.026	0.147	0.005
Surf	32	0.047	0.061	0.977	0.024	0.369	0.003
	64	0.146	0.086	0.905	0.023	0.158	0.005
	96	0.160	0.101	0.915	0.016	0.214	0.001
	128	0.202	0.149	−3.447	0.039	0.229	0.008
Cheer	64	0.168	0.049	0.027	0.831	0.293	0.001
	96	0.167	0.015	0.008	0.982	0.470	0.001
	128	0.250	0.090	0.058	−4.341	0.456	0.003
Tide	32	0.071	0.085	0.050	0.022	1.007	0.002
	64	0.048	0.055	0.024	0.025	0.924	0.001
	96	0.045	0.063	0.016	0.026	1.086	0.001
	128	0.072	0.093	0.039	0.045	−2.683	0.001
Solo	64	0.066	0.070	0.027	0.021	0.150	0.002
	96	0.219	0.032	0.023	0.033	0.075	0.000
	128	0.127	0.125	0.060	0.043	0.302	0.001
Era	32	0.035	0.155	0.039	0.022	0.425	0.000
	64	0.030	0.103	0.039	0.018	0.304	0.008
	96	0.035	0.168	0.033	0.027	0.352	0.001
	128	0.054	0.192	0.061	0.029	0.513	0.014
Private	64	0.123	0.119	0.066	0.039	0.081	0.248
label	128	0.174	0.266	0.100	0.019	0.072	−2.682
No purchase		0.007	0.002	0.004	0.000	0.013	0.000

[a]Cell entries i and j, where i indexes row and j indexes column, give the percent change in market share of brand i with a 1 percent change in the price of j. All columns are for a 128 oz. product, the most popular size. The results are based on Tables IV–VI.

[b]Note that "All" is the name of a detergent produced by Unilever.

forgone purchases due to the higher price level. Namely, the proportion of purchases that, due to the permanent increase in the price of 128 oz. Tide (i.e., an increase in the support of the whole price process), lead to no purchase at all. In contrast, one would expect the response to a short-run price increase to be a lot larger. The reaction to a temporary price change includes not only the reduction in purchases, but also the change in the timing of the immediate purchase due to the temporary price change. As we discuss next, we indeed find that short-run estimates overestimate the substitution to the outside option. This highlights the bias from static estimates that our framework overcomes.

We next compare the long-run elasticities to elasticities computed from static demand models. There are two reasons why these will differ. First, the coefficients estimated in the static model are (upward) biased and inconsistent because of the omitted inventory and expectations. Even with the right controls, static estimation would reveal short-run responses. The dynamic model is needed to separate inventory responses to short-run price changes from consumption changes and brand substitutions in response to long-run price changes.

Table VIII presents the ratio of the static estimates to the dynamic estimates. Cell entries i and j, where i indexes row and j indexes column, give the ratio of the (short-run) elasticities computed from a static model divided by the long-run elasticities computed from the dynamic model. The elasticities for both models are the percent change in market share of brand i with a 1 percent change in the price of j. The static model is identical to the model estimated in the first step except that brands of all sizes are included as well as a no-purchase decision, not just products of the same size as the chosen option. The estimates from the dynamic model are based on the results presented in Tables IV–VI. The elasticities are evaluated at each of the observed data points, the ratio is taken and then averaged over the observations.

The results suggest that the static own-price elasticities overestimate the dynamic ones by roughly 30 percent. Part of this difference is driven by the bias in the estimates of the static model. The price coefficient estimated in the static model is roughly 15 percent higher than that estimated in the first stage of the dynamic model. This ratio varies slightly across brands and also across the main sizes, 64 and 128 oz.

In contrast, the static cross-price elasticities, with the exception of the no-purchase option, are smaller than the long-run elasticities. The effect on the no-purchase option is expected because the static model fails to account for the effect of inventory. A short-run price increase is most likely to chase away consumers who can wait for a better price, namely those with high inventories. Therefore, the static model will overestimate the substitution to the no-purchase option.

There are several effects that impact the cross-price elasticities to the other brands. As we previously noted, the coefficients estimated in the static model will tend to be upward biased. This suggests that the elasticities estimated from the dynamic model will be larger in magnitude. However, there is an additional effect due to the difference between long-run and short-run effects. Consider a reduction in the price of Tide. The static elasticities are computed from data that had temporary price reductions. Switchers are those households that are willing to switch, for example, from Cheer *and* have a low enough inventory at the time of the price change. In contrast, the long-run elasticities capture those households that are willing to substitute at all relevant levels of inventory, because they represent reactions to a permanent change in the price of Tide.

In the case of the own-price effect as well as in the case of cross-price effects toward the no-purchase option, the econometric bias and the difference

TABLE VIII

AVERAGE RATIOS OF ELASTICITIES COMPUTED FROM A STATIC MODEL TO LONG-RUN ELASTICITIES COMPUTED FROM THE DYNAMIC MODEL[a]

		64 oz.						128 oz.					
Brand	Size (oz.)	All[b]	Wisk	Surf	Cheer	Tide	Private Label	All[b]	Wisk	Surf	Cheer	Tide	Private Label
All[b]	64	1.03	0.13	0.14	0.12	0.13	0.15	0.14	0.17	0.17	0.18	0.21	0.34
	128	0.17	0.24	0.26	0.20	0.28	0.35	1.23	0.09	0.11	0.09	0.15	0.22
Wisk	64	0.14	1.20	0.13	0.17	0.12	0.13	0.16	0.22	0.14	0.22	0.25	0.20
	128	0.25	0.27	0.23	0.31	0.26	0.28	0.08	1.42	0.08	0.13	0.18	0.11
Surf	64	0.14	0.13	0.93	0.16	0.13	0.14	0.18	0.18	0.12	0.18	0.22	0.28
	128	0.25	0.22	0.18	0.27	0.25	0.18	0.12	0.11	1.20	0.08	0.15	0.14
Cheer	64	0.12	0.17	0.16	0.84	0.09	0.13	0.14	0.24	0.16	0.14	0.22	0.24
	128	0.25	0.26	0.26	0.12	0.23	0.22	0.09	0.12	0.06	0.89	0.15	0.07
Tide	64	0.16	0.17	0.13	0.13	1.26	0.15	0.22	0.28	0.16	0.26	0.22	0.37
	128	0.25	0.31	0.22	0.24	0.22	0.31	0.11	0.16	0.08	0.13	1.44	0.31
Solo	64	0.15	0.12	0.15	0.14	0.12	0.14	0.17	0.15	0.15	0.30	0.30	0.28
	128	0.23	0.20	0.24	0.21	0.21	0.25	0.07	0.07	0.06	0.16	0.17	0.21
Era	64	0.21	0.12	0.13	0.13	0.10	0.19	0.43	0.17	0.15	0.22	0.19	0.35
	128	0.31	0.22	0.24	0.25	0.17	0.38	0.19	0.08	0.09	0.11	0.10	0.22
Private	64	0.19	0.15	0.14	0.17	0.17	1.02	0.32	0.22	0.15	0.26	0.31	0.25
label	128	0.29	0.28	0.34	0.30	0.39	0.29	0.16	0.12	0.13	0.10	0.27	1.29
No purchase		2.12	1.13	1.15	1.40	1.27	2.39	1.80	7.60	2.26	14.11	2.38	10.86

[a]Cell entries i and j, where i indexes row and j indexes column, give the ratio of the (short-run) elasticities computed from a static model divided by the long-run elasticities computed from the dynamic model. The elasticities for both models are the percent change in market share of brand i with a 1 percent change in the price of j. The static model is identical to the model estimated in the first step, except that brands of all sizes are included as well as a no-purchase decision, not just products of the same size as the chosen option. The results from the dynamic model are based on the results presented in Tables IV–VI.

[b]Note that "All" is the name of a detergent produced by Unilever.

between short- and long- run effects operate in the same direction. Both overstate price responses. However, it is unclear which one of the effects (that work in opposite directions) dominates in the case of cross-price elasticities (toward other goods). It depends on the relative size of the two effects and whether the observed price variation was temporary or more permanent in nature. In our data, the latter effect dominates.

One might wonder about the representativeness of the results from our sample. The sample may not be representative of the whole population because it records detergent purchases in supermarkets only. Moreover, the sample we selected in the estimation may not reflect the whole population that purchases in supermarkets. The answer depends on the question one wishes to answer. We care about the ratio of elasticities for the typical consumer. We are likely underestimating the importance of consumer inventory because many of the consumers who shop elsewhere (e.g., at Walmart or Costco) will not be in our sample; these are the consumers more likely to buy for inventory. Alternatively, we might care about the typical shopper at the supermarkets in the sample. In other words, what is the long-run elasticity of the demand faced by the supermarkets. To evaluate how representative our selected sample is (of the whole population buying at these supermarkets), we estimated a static demand system using the aggregate data (namely, using total weekly sales at the store level, not just from the households in our sample). We found results similar to the static demand estimated using the household sample. This leads us to conclude that the results from our sample are reasonably representative.

Estimates of the demand elasticities are often used in one of two ways. They are used in a first-order condition, typically from a Bertrand pricing game, to compute price–cost margins (PCM). For single product firms, it is straightforward to see the magnitude of the bias: it is the same as the ratio of own-price elasticities. Therefore, the numbers in Table VIII suggest that for single product firms, the PCM computed from the dynamic estimates will be roughly 30 percent higher than those computed from static estimates. The bias is even larger for multiproduct firms because the dynamic model finds that the products are closer substitutes (and therefore a multiproduct firm would want to raise their prices even further) than the static estimates suggest.

PCM computed in this way are used to test among different supply models; in particular they are used to test for tacit collusion in prices (e.g., Bresnahan (1987) or Nevo (2001)). Static estimates will tend to find evidence of collusion where there is none, because the PCM predicted by models without collusion will seem too low.

Another use of demand estimates is to simulate the effects of mergers (e.g., Hausman, Leonard, and Zona (1994) and Nevo (2000)). The numbers in Table VIII suggest that estimates from a static model would tend to underestimate the effects of a merger, because they tend to underestimate the substitution among products. Furthermore, because the static estimates overestimate the substitution to the outside good if used to define the market, then they will

tend to define it larger than a definition based on the dynamic estimates. In either case, the static estimates will favor approval of mergers.

6. CONCLUDING REMARKS

In this paper we structurally estimate a model of household inventory holding, allowing for product differentiation, sales, advertising, and nonlinear prices. The estimates suggest that ignoring the dynamics dictated by the ability to time purchases can lead to biased demand estimates. We find that static estimates overestimate own-price elasticities, underestimate cross-price responses to other products, and overestimate the substitution toward no purchase.

An implication of the model is that the likelihood of the observed choices can be split between a dynamic and a static component. We estimate the latter independently at little computational cost. The dynamic component requires the usual computation burden (of numerically solving the dynamic programming and numerically searching for the parameters that maximize the likelihood). However, the computational burden is substantially reduced by the split of the likelihood: we solve a simplified problem that involves only a quantity choice.

This split of the likelihood suggests a simple shortcut that can be used to reduce the biases that arise in a static estimation. The shortcut involves estimating demand conditional on the actual quantity purchased. In our case, the shortcut eliminates most of the short-run biases.

The estimates suggest differences between the long-run price effects computed from the dynamic model and a static one. Our static estimation used high frequency weekly consumer-level data. We also examined aggregate weekly data and got similar results. A common approach in the literature is to use monthly or quarterly aggregate data with the hope that aggregation over time smooths away the effects of temporary price reductions. An open question is how the results from static estimation using less frequent data compare to the dynamic results. A somewhat related question is whether there is a simple way to adjust the static estimation through time aggregation, much like the shortcut discussed in the previous paragraph, to attenuate the biases.

This paper neglected the supply side of the market. Future work could use estimates of demand to simulate profits from different pricing policies to evaluate, for instance, the profitability of observed sales. One of the key difficulties is setting up the agent's problem in a tractable way. A compact and tractable representation of the aggregate demand, as discussed in the previous paragraph, will be helpful.

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APPENDIX

In this appendix we provide proofs to some of the claims made in the text. First, we show that, conditional on size purchased, optimal consumption is the same regardless of which brand is purchased. Let $c_k^*(x_t, \nu_t)$ be the optimal consumption conditional on a realization of ν_t and purchase of size x_t of brand k.

LEMMA 1: $c_j^*(x_t, \nu_t) = c_k^*(x_t, \nu_t)$.

PROOF: Suppose there exists j and k such that $c_j^* = c_j^*(x_t, \nu_t) \neq c_k^*(x_t, \nu_t) = c_k^*$. Then

$$\begin{aligned}
&\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + \varepsilon_{jxt} + u(c_j^* + \nu_t) - C(i_t + x_t - c_j^*) \\
&\quad + \delta E(V(s_t)|d_{jt} = 1, x_t, c_j^*) \\
&\quad > \alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + \varepsilon_{jxt} + u(c_k^* + \nu_t) - C(i_t + x_t - c_k^*) \\
&\quad + \delta E(V(s_t)|d_{jt} = 1, x_t, c_k^*)
\end{aligned}$$

and, therefore,

$$\begin{aligned}
&u(c_j^* + \nu_t) - u(c_k^* + \nu_t) \\
&\quad > \delta E(V(s_t)|d_{jt} = 1, x_t, c_k^*) - \delta E(V(s_t)|d_{jt} = 1, x_t, c_j^*) \\
&\quad + C(i_t + x_t - c_k^*) - C(i_t + x_t - c_j^*).
\end{aligned}$$

Similarly, from the definition of $c_k^*(x_t, \nu_t)$,

$$\begin{aligned}
&u(c_j^* + \nu_t) - u(c_k^* + \nu_t) \\
&\quad < \delta E(V(s_t)|d_{jt} = 1, x_t, c_k^*) - \delta E(V(s_t)|d_{jt} = 1, x_t, c_j^*) \\
&\quad + C(i_t + x_t - c_k^*) - C(i_t + x_t - c_j^*),
\end{aligned}$$

which is a contradiction. *Q.E.D.*

PROOF OF CLAIM 1: The dynamic problem defined in equation (1) has an associated Bellman equation

$$V(s_t) = \operatorname*{Max}_{\{c, d_{jx}\}} \left\{ u(c + \nu_t) - C(i_{t+1}) + \sum_{j,x} d_{jx}(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + \varepsilon_{jxt}) + \delta E[V(s_{t+1})|s_t, c, d_{jx}] \right\}.$$

From Assumptions 1 and 3, both ε and ν are independently and identically distributed. Moreover, current actions affect future utility only through end-of-period inventory, so we can write $E[V(s_{t+1})|i_t, p_t, c, d_{jx}]$. In other words, the expectation of V given the state and current behavior is a function of current price and end-of-period inventories. Let us denote such a function as $V^e(i_{t+1}, p_t)$.

Taking expectations of $V(s_t)$ given the information available at $t-1$ (which includes actions taken at $t-1$), we can find $V^e(i_t, p_{t-1})$. Using the independence of ε, ν, and p, we get

$$\begin{aligned} &V^e(i_t, p_{t-1}) \\ &\quad = \int \Bigg[\operatorname*{Max}_{\{c, d_{jx}\}} \Bigg\{ u(c+\nu_t) - C(i_{t+1}) + \sum_{j,x} d_{jx}(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + \varepsilon_{jxt}) \\ &\qquad + \delta V^e(i_t + x - c, p_t) \Bigg\} \Bigg] dF(\varepsilon)\, dF(\nu)\, dF(p_t|p_{t-1}). \end{aligned}$$

By Lemma 1, optimal consumption depends on the quantity purchased, but not on the brand chosen; then $\operatorname{Max}_c\{u(c+\nu_t) - C(i_{t+1}) + \delta V^e(i_t + x - c, p_t)\}$ varies by size x, but is independent of choice of brand j. Denote this function $M(s_t, x)$. Therefore,

$$\begin{aligned} V^e(i_t, p_{t-1}) = \int \Bigg[\operatorname*{Max}_{d_{xj}} \Bigg(&\sum_{j,x} d_{jx}(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + \varepsilon_{jxt}) \\ &+ M(s_t, x) \Bigg) \Bigg] dF(\varepsilon)\, dF(\nu)\, dF(p_t|p_{t-1}). \end{aligned}$$

For the case of extreme value shocks (see McFadden (1981)) and using the definition of the inclusive values given in equation (5), this last expression can be written as

$$V^e(i_t, p_{t-1}) = \int \log\Bigg(\sum_x \exp(\omega_{xt} + M(s_t, x)) \Bigg) dF(\nu)\, dF(p_t|p_{t-1}).$$

Using Assumption 4, V^e can be written as a function of ω_t and i_t instead of p_t and i_t, leading to (spelling out the function M to remind the reader)

$$\begin{aligned} V^e(i_t, \omega_{t-1}) = \int \log\Bigg(&\sum_x \exp\big(\omega_{xt} + \operatorname*{Max}_c \big\{ u(c+\nu_t) - C(i_{t+1}) \\ &+ \delta V^e(i_{t+1}, \omega_t) \big\}\big) \Bigg) dF(\nu)\, dF(\omega_t|\omega_{t-1}). \end{aligned}$$

The former functional equation can be used to find $V^e(i_t, \omega_{t-1})$.

Notice that $V^e(i_t, \omega_{t-1})$ also characterizes the problem

$$V(i_t, \omega_{t-1}, \varepsilon_t, \nu_t) = \underset{\{c,x\}}{\text{Max}}\{u(c+\nu_t) - C(i_{t+1}) + \omega_{xt} + \varepsilon_{xt} + \delta V^e(i_{t+1}, \omega_t)\}.$$

This can be seen by taking expectations with respect to ε on the right-hand side. Notice that this last Bellman equation characterizes the optimal behavior of a consumer who chooses x (quantity purchased) in every period, enjoying a shock $\varepsilon_{xt} + w_{xt}$ from buying quantity x in period t.

Finally, we want to show that we can rely on $V^e(i_t, \omega_{t-1})$ to derive the likelihood of purchase of quantity x. We want to show that

$$\Pr(x_t|i_t, p_t, \nu_t) = \Pr(x_t|i_t, \omega(p_t), \nu_t).$$

Notice that

$$\Pr(x_t|i_t, \omega_t, \nu_t) = \frac{\exp(\omega_{xt} + \text{Max}_{c_t}\{u(c_t+\nu_t) - C(i_{t+1}) + \delta V^e(i_{t+1}, \omega_t)\})}{\sum_x \exp(\omega_{xt} + \text{Max}_{c_t}\{u(c_t+\nu_t) - C(i_{t+1}) + \delta V^e(i_{t+1}, \omega_t)\})},$$

whereas

$$\begin{aligned}
&\Pr(x_t|p_t, i_t, \nu_t) \\
&= \frac{\sum_j \exp(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt} + M(s_t, x))}{\sum_j \exp(\alpha p_{jyt} + \xi_{jy} + \beta a_{jyt} + M(s_t, x))} \\
&= \frac{\exp(M(s_t, x)) \exp(\log(\sum_j \exp(\alpha p_{jxt} + \xi_{jx} + \beta a_{jxt})))}{\sum_y \exp(M(s_t, y)) \exp(\log(\sum_j \exp(\alpha p_{jyt} + \xi_{jy} + \beta a_{jyt})))} \\
&= \frac{\exp(\omega_{xt} + M(s_t, x))}{\sum_y \exp(\omega_{yt} + M(s_t, y))} \\
&= \Pr(x_t|\omega_t, i_t, \nu_t),
\end{aligned}$$

where the last equality follows from the fact the M depends on ω but not on p. *Q.E.D.*

REFERENCES

AGUIRREGABIRIA, V. (1999): "The Dynamics of Markups and Inventories in Retailing Firms," *The Review of Economic Studies*, 66, 275–308. [1639]

——— (2005): "Nonparametric Identification of Behavioral Responses to Counterfactual Policy Interventions in Dynamic Discrete Decision Processes," *Economics Letters*, 87, 393–398. [1653]

AILAWADI, K. L., AND S. NESLIN (1998): "The Effect of Promotion on Consumption: Buying More and Consuming It Faster," *Journal of Marketing Research*, 35, 390–398. [1640,1644]

BELL, D., AND Y. BOZTUG (2004): "The Effect of Inventory on Purchase Incidence: Empirical Analysis of Opposing Forces of Storage and Consumption," Mimeo, Wharton School, University of Pennsylvania. [1640,1644]

BELL, D., J. CHIANG, AND V. PADMANABHAN (1999): "The Decomposition of Promotional Response: An Empirical Generalization," *Marketing Science*, 18, 504–526. [1640]

BENITEZ-SILVA, H., G. HALL, G. HITSCH, G. PAULETTO, AND J. RUST (2000): "A Comparison of Discrete and Parametric Approximation Methods for Continuous-State Dynamic Programming Problems," Mimeo, Yale University. [1652]

BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841–890. [1637]

BERTSEKAS, D., AND J. TSITSIKLIS (1996): *Neuro-Dynamic Programming*. Cambridge, MA: Athena Scientific. [1652]

BLATTBERG, R., G. EPPEN, AND J. LIEBERMAN (1981): "A Theoretical and Empirical Evaluation of Price Deals in Consumer Nondurables," *Journal of Marketing*, 45, 116–129. [1639,1640]

BOIZOT, C., J.-M. ROBIN, AND M. VISSER (2001): "The Demand for Food Products. An Analysis of Interpurchase Times and Purchased Quantities," *Economic Journal*, 111, 391–419. [1639]

BRESNAHAN, T. (1987): "Competition and Collusion in the American Automobile Oligopoly: The 1955 Price War," *Journal of Industrial Economics*, 35, 457–482. [1637,1667]

CHIANG, J. (1991): "A Simultaneous Approach to the Whether, What and How Much to Buy Questions," *Marketing Science*, 10, 297–315. [1640]

CHAMBERLAIN, G. (1983): "Panel Data," in *Handbook of Econometrics*, ed. by Z. Griliches and M. Intrilligator. Amsterdam: North-Holland. [1655]

CURRIM, I., AND L. SCHNEIDER (1991): "A Taxonomy of Consumer Purchase Strategies in a Promotion Intense Environment," *Marketing Science*, 10, 91–110. [1639,1640]

ERDEM, T., S. IMAI, AND M. KEANE (2003): "Consumer Price and Promotion Expectations: Capturing Consumer Brand and Quantity Choice Dynamics under Price Uncertainty," *Quantitative Marketing and Economics*, 1, 5–64. [1638,1639,1655,1657]

GUPTA, S. (1988): "Impact of Sales Promotions on when, What, and How Much to Buy," *Journal of Marketing Research*, 24, 342–355. [1640]

——— (1991): "Stochastic Models of Interpurchase Time with Time-Dependent Covariates," *Journal of Marketing Research*, 28, 1–15. [1640]

HAUSMAN, J., G. LEONARD, AND J. D. ZONA (1994): "Competitive Analysis with Differentiated Products," *Annales d'Economie et de Statistique*, 34, 159–180. [1637,1667]

HENDEL, I., AND A. NEVO (2006): "Sales and Consumer Stockpiling," *The RAND Journal of Economics*, forthcoming. [1643,1644]

HOSKEN, D., D. MATSA, AND D. REIFFEN (2000): "How Do Retailers Adjust Prices: Evidence from Store-Level Data," Working Paper 230, Federal Trade Commission Bureau of Economics. [1639]

LUCAS, R. E., AND L. A. RAPPING (1969): "Real Wages Employment, and Inflation," *The Journal of Political Economy*, 77, 721–754. [1637]

MAGNAC, T., AND D. THESMAR (2002): "Identifying Dynamic Discrete Decision Processes," *Econometrica*, 70, 801–816. [1653]

MCFADDEN, D. (1981): "Econometric Models of Probabilistic Choice," in *Structural Analysis of Discrete Data*, ed. by C. Manski and D. McFadden. Cambridge, MA: MIT Press, 198–272. [1651, 1670]

MELNIKOV, O. (2001): "Demand for Differentiated Durable Products: The Case of the U.S. Computer Printer Market," Mimeo, Cornell University. [1649]

MURPHY, K., AND R. TOPEL (1985): "Estimation and Inference in Two-Step Econometric Models," *Journal of Business & Economics Statistics*, 3, 370–379. [1656]

NESLIN, S., C. HENDERSON, AND J. QUELCH (1985): "Consumer Promotions and the Acceleration of Product Purchases," *Marketing Science*, 4, 147–165. [1639,1640]

NESLIN, S., AND L. SCHNEIDER STONE (1996): "Consumer Inventory Sensitivity and the Postpromotion Dip," *Marketing Letters*, 7, 77–94. [1640]

NEVO, A. (2000): "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry," *The RAND Journal of Economics*, 31, 395–421. [1667]

——— (2001): "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica*, 69, 307–342. [1667]

PESENDORFER, M. (2002): "Retail Sales. A Study of Pricing Behavior in Supermarkets," *Journal of Business*, 75, 33–66. [1639]

RUST, J. (1987): "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55, 999–1033. [1638,1647]

——— (1996): "Numerical Dynamic Programming in Economics," in *Handbook of Computational Economics*, Vol. 1, ed by. H. Amman, D. Kendrick, and J. Rust. Amsterdam: North-Holland, 619–729. [1653]

SHOEMAKER, R. W. (1979): "An Analysis of Consumer Reactions of Product Promotions," in *Educators' Conference Proceedings*. Chicago: American Marketing Association, 244–248. [1639]

TRAIN, K. (1986): *Qualitative Choice Analysis: Theory, Econometrics and Application to Automobile Demand*. Cambridge, MA: MIT Press. [1649]

EXHIBIT 9

Merger Guidelines

U.S. Department of Justice and the Federal Trade Commission

Issued: December 18, 2023

B. Direct evidence of the exercise of market power can demonstrate the existence of a relevant market in which that power exists. This evidence can be valuable when assessing the risk that a dominant position may be entrenched, maintained, or extended, since the same evidence identifies market power and can be sufficient to identify the line of commerce and section of the country affected by a merger, even if the metes and bounds of the market are only broadly characterized.

C. A relevant market can be identified from evidence on observed market characteristics ("practical indicia"), such as industry or public recognition of the submarket as a separate economic entity, the product's peculiar characteristics and uses, unique production facilities, distinct customers, distinct prices, sensitivity to price changes, and specialized vendors.[80] Various practical indicia may identify a relevant market in different settings.

D. Another common method employed by courts and the Agencies is the hypothetical monopolist test.[81] This test examines whether a proposed market is too narrow by asking whether a hypothetical monopolist over this market could profitably worsen terms significantly, for example, by raising price. An analogous hypothetical monopsonist test applies when considering the impact of a merger on competition among buyers.

The Agencies use these tools to define relevant markets because they each leverage market realities to identify an area of effective competition.

Section 4.3.A below describes the Hypothetical Monopolist Test in greater detail. Section 4.3.B addresses issues that may arise when defining relevant markets in several specific scenarios.

4.3.A. The Hypothetical Monopolist Test

This Section describes the Hypothetical Monopolist Test, which is a method by which the Agencies often define relevant antitrust markets. As outlined above, a relevant antitrust market is an area of effective competition. The Hypothetical Monopolist/Monopsonist Test ("HMT") evaluates whether a group of products is sufficiently broad to constitute a relevant antitrust market. To do so, the HMT asks whether eliminating the competition among the group of products by combining them under the control of a hypothetical monopolist likely would lead to a worsening of terms for customers. The Agencies generally focus their assessment on the constraints from competition, rather than on constraints from regulation, entry, or other market changes. The Agencies are concerned with the impact on economic incentives and assume the hypothetical monopolist would seek to maximize profits.

When evaluating a merger of sellers, the HMT asks whether a hypothetical profit-maximizing firm, not prevented by regulation from worsening terms, that was the only present and future seller of a group of products ("hypothetical monopolist") likely would undertake at least a small but significant and non-transitory increase in price ("SSNIP") or other worsening of terms ("SSNIPT") for at least one

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[80] *Brown Shoe*, 370 U.S. at 325, *quoted in United States v. U.S. Sugar Corp.*, 73 F.4th 197, 204-07 (3d Cir. 2023) (affirming district court's application of *Brown Shoe* practical indicia to evaluate relevant product market that included, based on the unique facts of the industry, those distributors who "could counteract monopolistic restrictions by releasing their own supplies").

[81] *See FTC v. Penn State Hershey Med. Center*, 838 F.3d 327, 338 (3d Cir. 2016). While these guidelines focus on applying the hypothetical monopolist test in analyzing mergers, the test can be adapted for similar purposes in cases involving alleged monopolization or other conduct. *See, e.g.*, *McWane, Inc. v. FTC*, 783 F.3d 814, 829-30 (11th Cir. 2015).

product in the group.[82] For the purpose of analyzing this issue, the terms of sale of products outside the candidate market are held constant. Analogously, when considering a merger of buyers, the Agencies ask the equivalent question for a hypothetical monopsonist. This Section often focuses on merging sellers to simplify exposition.

4.3.B. Implementing the Hypothetical Monopolist Test

The SSNIPT. A SSNIPT may entail worsening terms along any dimension of competition, including price (SSNIP), but also other terms (broadly defined) such as quality, service, capacity investment, choice of product variety or features, or innovative effort.

Input and Labor Markets. When the competition at issue involves firms buying inputs or employing labor, the HMT considers whether the hypothetical monopsonist would undertake at least a SSNIPT, such as a decrease in the offered price or a worsening of the terms of trade offered to suppliers, or a decrease in the wage offered to workers or a worsening of their working conditions or benefits.

The Geographic Dimension of the Market. The hypothetical monopolist test is generally applied to a group of products together with a geographic region to determine a relevant market, though for ease of exposition the two dimensions are discussed separately, with geographic market definition discussed in Section 4.3.D.2.

Negotiations or Auctions. The HMT is stated in terms of a hypothetical monopolist *undertaking* a SSNIPT. This covers settings where the hypothetical monopolist sets terms and makes them worse. It also covers settings where firms bargain, and the hypothetical monopolist would have a stronger bargaining position that would likely lead it to extract a SSNIPT during negotiations, or where firms sell their products in an auction, and the bids submitted by the hypothetical monopolist would result in the purchasers of its products experiencing a SSNIPT.

Benchmark for the SSNIPT. The HMT asks whether the hypothetical monopolist likely would worsen terms relative to those that likely would prevail absent the proposed merger. In some cases, the Agencies will use as a benchmark different outcomes than those prevailing prior to the merger. For example, if outcomes are likely to change absent the merger, e.g., because of innovation, entry, exit, or exogenous trends, the Agencies may use anticipated future outcomes as the benchmark. Or, if suppliers in the market are coordinating prior to the merger, the Agencies may use a benchmark that reflects conditions that would arise if coordination were to break down. When evaluating whether a merging firm is dominant (Guideline 6), the Agencies may use terms that likely would prevail in a more competitive market as a benchmark.[83]

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[82] If the pricing incentives of the firms supplying the products in the group differ substantially from those of the hypothetical monopolist, for reasons other than the latter's control over a larger group of substitutes, the Agencies may instead employ the concept of a hypothetical profit-maximizing cartel comprised of the firms (with all their products) that sell the products in the candidate market. This approach is most likely to be appropriate if the merging firms sell products outside the candidate market that significantly affect their pricing incentives for products in the candidate market. This could occur, for example, if the candidate market is one for durable equipment and the firms selling that equipment derive substantial net revenues from selling spare parts and service for that equipment. Analogous considerations apply when considering a SSNIPT for terms other than price.

[83] In the entrenchment context, if the inquiry is being conducted after market or monopoly power has already been exercised, using prevailing prices can lead to defining markets too broadly and thus inferring that dominance does not exist when, in

Magnitude of the SSNIPT. What constitutes a "small but significant" worsening of terms depends upon the nature of the industry and the merging firms' positions in it, the ways that firms compete, and the dimension of competition at issue. When considering price, the Agencies will often use a SSNIP of five percent of the price charged by firms for the products or services to which the merging firms contribute value. The Agencies, however, may consider a different term or a price increase that is larger or smaller than five percent.[84]

The Agencies may base a SSNIP on explicit or implicit prices for the firms' specific contribution to the value of the product sold, or an upper bound on the firms' specific contribution, where these can be identified with reasonable clarity. For example, the Agencies may derive an implicit price for the service of transporting oil over a pipeline as the difference between the price the pipeline firm paid for oil at one end and the price it sold the oil for at the other and base the SSNIP on this implicit price.

4.3.C. Evidence and Tools for Carrying Out the Hypothetical Monopolist Test

Section 4.2 describes some of the qualitative and quantitative evidence and tools the Agencies can use to assess the extent of competition among firms. The Agencies can use similar evidence and analogous tools to apply the HMT, in particular to assess whether competition among a set of firms likely leads to better terms than a hypothetical monopolist would undertake.

To assess whether the hypothetical monopolist likely would undertake at least a SSNIP on one or more products in the candidate market, the Agencies sometimes interpret the qualitative and quantitative evidence using an economic model of the profitability to the hypothetical monopolist of undertaking price increases; the Agencies may adapt these tools to apply to other forms of SSNIPTs.

One approach utilizes the concept of a "recapture rate" (the percentage of sales lost by one product in the candidate market, when its price alone rises, that is recaptured by other products in the candidate market). A price increase is profitable when the recapture rate is high enough that the incremental profits from the increased price plus the incremental profits from the recaptured sales going to other products in the candidate market exceed the profits lost when sales are diverted outside the candidate market. It is possible that a price increase is profitable even if a majority of sales are diverted outside the candidate market, for example if the profits on the lost sales are relatively low or the profits on the recaptured sales are relatively high.

Sometimes evidence is presented in the form of "critical loss analysis," which can be used to assess whether undertaking at least a SSNIPT on one or more products in a candidate market would raise or lower the hypothetical monopolist's profits. Critical loss analysis compares the magnitude of the two offsetting effects resulting from the worsening of terms. The "critical loss" is defined as the number of lost unit sales that would leave profits unchanged. The "predicted loss" is defined as the number of unit sales that the hypothetical monopolist is predicted to lose due to the worsening of terms. The worsening of terms raises the hypothetical monopolist's profits if the predicted loss is less than the

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fact, it does. The problem with using prevailing prices to define the market when a firm is already dominant is known as the "Cellophane Fallacy."

[84] The five percent price increase is not a threshold of competitive harm from the merger. Because the five percent SSNIP is a minimum expected effect of a hypothetical monopolist of an *entire* market, the actual predicted effect of a merger within that market may be significantly lower than five percent. A merger within a well-defined market that causes undue concentration can be illegal even if the predicted price increase is well below the SSNIP of five percent.

critical loss. While this "breakeven" analysis differs somewhat from the profit-maximizing analysis called for by the HMT, it can sometimes be informative.

The Agencies require that estimates of the predicted loss be consistent with other evidence, including the pre-merger margins of products in the candidate market used to calculate the critical loss. Unless the firms are engaging in coordinated interaction, high pre-merger margins normally indicate that each firm's product individually faces demand that is not highly sensitive to price. Higher pre-merger margins thus indicate a smaller predicted loss as well as a smaller critical loss. The higher the pre-merger margin, the smaller the recapture rate[85] necessary for the candidate market to satisfy the hypothetical monopolist test. Similar considerations inform other analyses of the profitability of a price increase.

4.3.D. Market Definition in Certain Specific Settings

This Section provides details on market definition in several specific common settings. In much of this section, concepts are presented for the scenario where the merger involves sellers. In some cases, clarifications are provided as to how the concepts apply to merging buyers; in general, the concepts apply in an analogous way.

4.3.D.1. Targeted Trading Partners

If the merged firm could profitably target a subset of customers for changes in prices or other terms, the Agencies may identify relevant markets defined around those targeted customers. The Agencies may do so even if firms are not currently targeting specific customer groups but could do so after the merger.

For targeting to be feasible, two conditions typically must be met. First, the suppliers engaging in targeting must be able to set different terms for targeted customers than other customers. This may involve identification of individual customers to which different terms are offered or offering different terms to different types of customers based on observable characteristics.[86] Markets for targeted customers need not have precise metes and bounds. In particular, defining a relevant market for targeted customers sometimes requires a line-drawing exercise on observable characteristics. There can be many places to draw that line and properly define a relevant market. Second, the targeted customers must not be likely to defeat a targeted worsening of terms by arbitrage (e.g., by purchasing indirectly from or through other customers). Arbitrage may be difficult if it would void warranties or make service more difficult or costly for customers, and it is inherently impossible for many services. Arbitrage on a modest scale may be possible but sufficiently costly or limited, for example due to transaction costs or search costs, that it would not deter or defeat a discriminatory pricing strategy.

If prices are negotiated or otherwise set individually, for example through a procurement auction, there may be relevant markets that are as narrow as an individual customer. Nonetheless, for analytic convenience, the Agencies may define cluster markets for groups of targeted customers for whom the

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[85] The recapture rate is sometimes referred to as the aggregate diversion ratio, defined in Section 4.2.B.

[86] In some cases, firms offer one or more versions of products or services defined by their characteristics (where brand might be a characteristic). When customers can select among these products and terms do not vary by customer, the Agencies will typically define markets based on products rather than the targeted customers. In such cases, relevant antitrust markets may include only some of the differentiated products, for example products with only "basic" features, or products with "premium features." The tools described in Section 4.2 can be used to assess competition among differentiated products.

EXHIBIT 10

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UNITED STATES DISTRICT COURT

NORTHERN DISTRICT OF CALIFORNIA

SAN FRANCISCO DIVISION

MAXIMILIAN KLEIN, et al., on behalf of themselves and all others similarly situated, Plaintiffs, v. META PLATFORMS, INC., a Delaware Corporation headquartered in California, Defendant.	Case No. 3:20-cv-08570-JD **DEFENDANT META PLATFORMS, INC.'S RESPONSES AND OBJECTIONS TO CONSUMER PLAINTIFFS' FIFTH SET OF REQUESTS FOR PRODUCTION OF DOCUMENTS** Judge: Hon. James Donato

Pursuant to Rule 34 of the Federal Rules of Civil Procedure, Defendant Meta Platforms, Inc., by and through its attorneys, hereby submits the following responses and objections to Consumer Plaintiffs' Fifth Set of Requests for Production of Documents.

RESERVATION OF RIGHTS

Meta's responses are based solely on information currently available to Meta following a reasonable investigation and reflect Meta's investigation of facts and discovery of information and documents relating to the claims and defenses at issue in this case. Accordingly, Meta's responses to these Requests are based only upon Meta's current knowledge and reasonable belief. Investigation and discovery are ongoing. Nothing in these responses shall be deemed an admission by Meta of any information, or the relevance or admissibility of any information, for any purpose. Meta's agreement to produce any category of information or documents is not a representation that any such documents or information in that category actually exist in Meta's possession, custody, or control, or can be located through a reasonable search, or that such information or documents are relevant. Meta reserves all rights to supplement, revise, and/or amend these responses should additional information become available through the discovery process or other means. Meta reserves the right to make any use of, or to introduce at any hearing and at trial, information and/or documents responsive to the Requests but discovered subsequent to the date of their response, including, but not limited to, any such information or documents obtained in discovery herein. In responding to the Requests, Meta does not waive any objection on the ground of privilege, competency, relevance, materiality, authenticity, or admissibility of the information contained in these responses.

GENERAL OBJECTIONS

Meta hereby incorporates each of these general objections into its specific answers and objections to each of the Requests, whether or not Meta refers to such objection in its answer to a specific Request.

1. Meta objects to the Definitions and Instructions to the extent that they are broader than, or impose conditions, obligations, or duties that exceed or differ from those required by the

Federal Rules of Civil Procedure. Meta's responses are limited to the scope of the discovery set forth therein.

2. Meta objects to each Request for Production, Definition, and Instruction to the extent it is vague, ambiguous, overly broad, unduly burdensome, or seeks discovery of documents that are neither relevant to the claims or defenses of any party to this action nor proportional to the needs of the case.

3. Meta objects to each Request for Production, Definition, and Instruction to the extent it seeks documents that are outside of Meta's possession, custody, or control.

4. Meta objects to each Request for Production, Definition, and Instruction to the extent it seeks to require Meta to produce documents beyond what Meta is able to locate upon a reasonable search of its own files and from a reasonable inquiry of its current employees.

5. Meta objects to each Request for Production to the extent that it requests "all" data or information as overly broad and unduly burdensome.

6. Meta objects to each Request for Production as overly broad and unduly burdensome to the extent it fails to impose any reasonable limitation on the locations and custodians from whom documents are sought.

7. Meta objects to each Request for Production to the extent it seeks to require Meta to generate documents that do not already exist.

8. Meta objects to each Request for Production to the extent it seeks to require Meta to provide documents that are publicly available and/or equally available to Consumer Plaintiffs as to Meta.

9. Meta objects to each Request for Production to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-client privilege, work-product doctrine, or other applicable privilege. Meta intends to and does claim all such protections and privileges. To the extent privileged or protected documents are produced, such production is inadvertent and shall not constitute a waiver of any privilege or protection.

10. Meta objects to each Request for Production to the extent it seeks disclosure of

documents that Meta is under an obligation to a third party or court order not to disclose. To the extent Meta discovers any such responsive, nonprivileged information, it will disclose it only after complying with its obligations.

11. Meta objects to each Request for Production insofar as it seeks the production of documents that would violate the privacy rights of third parties; confidentiality or non-disclosure arrangements between Meta and any of its current or former employees, or other persons or entities not connected to this litigation; the confidentiality of settlement discussions or agreements; or any court orders restricting the disclosure of such documents.

12. Meta objects to each Request for Production to the extent it seeks information Meta is prohibited from disclosing under the Stored Communications Act, 18 U.S.C. § 2701 et seq.

13. Meta objects to each Request for Production to the extent that it is duplicative of any other discovery request.

14. Meta objects to each Request for Production to the extent that it is inconsistent with the Stipulated Protective Order (Dkt. 314), the First Amended Federal Rules of Evidence 502(d) Clawback Order (Dkt. 191), the Privilege Protocol (Dkt. 176), the Expert Protocol (Dkt. 175), the Deposition Protocol (Dkt. 174), the ESI Protocol (Dkt. 306), Judge Donato's Standing Orders, or any other Protocol or Order entered in this case.

OBJECTIONS TO DEFINITIONS AND INSTRUCTIONS

1. Meta objects to the definitions of "Document" and "Communication" to the extent they seek to impose any burden greater than those permitted under the Federal Rules of Civil Procedure.

2. Meta objects to the definitions of "Person" and "Persons" as overly broad, vague, ambiguous, and unduly burdensome, including because it purports to include entities outside of Meta's control and to the extent that it purports to require production of documents or information that are outside of Meta's possession, custody, or control and/or that are protected by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity

from disclosure.

3. Meta objects to the definition of "You" and "Your" and "Facebook" to the extent that it purports to require production of documents or information that are outside of Meta's possession, custody, or control and/or that are protected by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity from disclosure. Meta further objects to the definition of "Facebook" to the extent it creates ambiguity as to whether a particular request refers to Meta Platforms, Inc. (the corporate entity) or the Facebook platform. To avoid such ambiguity, Meta will refer to the corporate entity as "Meta" or "Meta Platforms" and to the platform as "Facebook" throughout its objections and responses.

4. Meta objects to the phrases "relate to," "related to," and "relating to" as overly broad, unduly burdensome, not proportional to the needs of the case, vague, and ambiguous, including but not limited to the definition extending "in any way" to the "subject matter of the Request."

5. Meta objects to Instructions No. 5 and No. 14 to the extent it seeks discovery of "all" documents without limitations for relevance or proportionality, in contravention of Federal Rule of Civil Procedure 26 and to the extent it purports to require production of documents or information that are outside of Meta's possession, custody, or control and/or that are protected by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity from disclosure.

6. Meta objects to Instruction No. 12 as overly broad, unduly burdensome, and disproportionate to the needs of the case to the extent it seeks discovery of documents created, generated, or containing information relating to a time period of over 14 years.

7. Meta objects to Instruction No. 13 to the extent it seeks discovery of materials in a manner inconsistent with the applicable ESI Protocol. Stipulated ESI Protocol, Dkt, No. 306.

8. Meta objects to the Instructions to the extent they require supplementation later in time than otherwise required under Federal Rule of Civil Procedure 26(e).

RESPONSES TO REQUESTS FOR PRODUCTION

REQUEST FOR PRODUCTION NO. 50:

Documents sufficient to show for each named plaintiff, the output file (zip archive and PDF) that is used by Your Law Enforcement Response Team (LERT) to respond to law enforcement requests for data and information regarding Facebook users.

RESPONSE TO REQUEST FOR PRODUCTION NO. 50:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta further objects to this Request to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-client privilege, or work-product doctrine, or other applicable privilege or immunity. Meta also objects to this Request as vague and ambiguous, including without limitation to the extent it relies on the term “output file.” Meta additionally objects to this Request to the extent that it seeks documents duplicative of material already produced to Plaintiffs, including the materials from Meta’s internal tool produced at PALM-016302325 through PALM-016410644. Meta further objects to this Request to the extent it seeks data pertaining to non-plaintiff users who have not consented to the release of their information in this litigation; such information has been redacted from the materials produced at PALM-016302325 through PALM-016410644. Meta also objects to this Request to the extent it seeks to require Meta to generate documents that do not already exist. And, Meta objects to this Request to the extent that it requests production of documents in a format inconsistent with the Stipulated ESI Protocol, Dkt, No. 306.

Subject to and without waiving its objections, Meta refers Plaintiffs to the documents it previously produced at PALM-016302325 through PALM-016410644.

REQUEST FOR PRODUCTION NO. 51:

Structured data for an anonymized sample of Facebook users (to be agreed upon between the parties) in the Consumer class of the following information on a daily basis:

A. User ID;

B. User characteristics, such as gender and age;

C. User geographic information;

D. Date;

E. Activity the user was engaged in (e.g., personal networking, watching videos, reading news);

F. The name of the platform on which the activity occurred (e.g., Facebook, Instagram, WhatsApp, Messenger);

G. Usage information, including types of content the user viewed or engaged with, features the user utilized, actions the user took, privacy settings the user selected, people or accounts the user interacted with, and time, frequency, and duration of these interactions and/or activities;

H. Number of ads served to the user during their Facebook activity;

I. All information about the user's off-Facebook activity gathered, received, or retained by Facebook, including sites or types of sites visited, purchases made, affinity ("Like" button) or other tracking information, and user characteristics inferred or categorizations defined based on off-Facebook activity, broken down by whether or not the user was logged into a Facebook site [or app] at the time;

J. Number of ads served by Facebook to the user during their off-Facebook activity;

K. Number of ads served by Facebook to the user based on their Facebook activity;

L. Number of ads served by Facebook to the user based on their off-Facebook activity;

M. Device category (mobile, tablets, PC);

N. Device type (e.g., iPhone, Android);

O. All data about the user shared with any third party, including but not limited to app developers, including the content of the data shared and the identity of the third party;

P. Any data about the user that Facebook learned or inferred from data about other users;

Q. Any data about the user that was used by Facebook to learn or infer data about other users; and

R. For each user in the sample, the data in this specification should be provided in raw form in which the information is maintained in the regular course of business and in summary form by applying the tools and methods that Facebook uses in the ordinary course of business to summarize the data that it collects on individual users.

RESPONSE TO REQUEST FOR PRODUCTION NO. 51:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this Request on the ground that it is overly broad, unduly burdensome, and not proportional to the needs of the case, including without limitation because this Request seeks more than 30 categories of information on a "daily basis" for a 14-year time period for some undefined set of Facebook users. Meta further objects to this Request on the ground that it is overly broad, unduly burdensome, and not proportional to the needs of the case, including without limitation because it requests "all" or "any" data or information. Meta further objects to this Request as vague and ambiguous, including without limitation to the extent it relies on the terms "geographic information," "activity," "shared," "features the users utilized," "usage information," "actions the user took," "based on," "off-Facebook activity," "tracking information," "user characteristics," "infer," "learn," "structured data," "raw form," "summary form," "number of ads," and "tools and methods," each of which is undefined and susceptible to more than one meaning. Meta further objects to this Request as unduly burdensome and not proportional to the needs of this case to the extent that it is cumulative of information sought in other Requests (including without limitation Request No. 52 of Consumer Plaintiffs' Fifth Set of Requests for Production) but purports to put the burden on Meta to produce cumulative information separately or in a different form. Meta additionally objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta further objects to this Request to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-

client privilege, work-product doctrine, or other applicable privilege or immunity. Meta objects to this Request as vague and ambiguous, including without limitation because it seeks information about ads that Meta served to Facebook users during their off-Facebook activity. And, Meta objects to this Request to the extent it seeks information about "any data" that Facebook "learned or inferred" or "was used by Facebook to learn or infer" about a user, as irrelevant to the issues in the case, and vague and ambiguous and, depending on the intended scope, overbroad, unduly burdensome and disproportionate to the needs of the case. Meta further objects to the instructions in Subpart R as overly broad, unduly burdensome, and disproportionate to the needs of the case to the extent that it purports to require duplicative and cumulative production of materials sought in other Requests, including without limitation this Request.

Subject to and without waiving its objections, Meta stands ready to meet and confer as to the scope of this Request. For the avoidance of doubt, Meta will not produce any documents in response to this Request unless and until the Parties have mutually agreed on the scope of production and subject matters implicated by this Request.

REQUEST FOR PRODUCTION NO. 52:

The following user metrics and statistics from January 2007 through the present (broken out by user characteristics, including but not limited to geographic location, gender, age group, education):

A. Daily, weekly, monthly, and annual average number of active users;

B. Daily time spent by activity (e.g., personal networking, watching videos, reading news);

C. Daily number of ads served to users; and

D. The above for each of Facebook's properties including but not limited to Facebook, Instagram, WhatsApp and Messenger.

RESPONSE TO REQUEST FOR PRODUCTION NO. 52:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this request on the ground that it is vague and ambiguous, and potentially overly broad, unduly burdensome, and disproportional to the needs of the case, including without limitation to the extent it fails to define the user population for which Consumer Plaintiffs seek these "user metrics and statics," some of which are requested on a "daily" basis. Meta further objects to this Request as overly broad, unduly burdensome, and not proportional to the needs of the case, including without limitation because it seeks data created over a more than 14-year period (which also predates Meta's acquisition of Instagram and WhatsApp, and the introduction of Messenger). Meta further objects to this Request as vague and ambiguous, including without limitation to the extent it relies on the terms "activity" and "number of ads," which are undefined and susceptible to more than one meaning and of an undefined scope. Meta further objects to this request as vague and ambiguous, including without limitation to the extent it seeks metrics and statistics for "each of Facebook's properties" for the period before Meta's acquisition of Instagram and WhatsApp, or the introduction of Messenger. Meta also objects to this Request as vague and ambiguous, including without limitation to the extent it seeks metrics and statistics regarding "ads served to users" without identifying a location for where the ad was served. Meta further objects to this Request as vague and ambiguous, including without limitation to the extent it relies on the terms "personal networking," "watching videos," and "reading news," "geographic location," "age group," and "education," each of which is undefined and susceptible to more than one meaning. Meta additionally objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta further objects to this Request to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity. Meta also objects to this Request as irrelevant, including without limitation to the extent that it seeks data for properties other than Facebook, when Users proposed putative class is defined as "All persons in the United States who maintained a Facebook profile at any point from 2007 up to the date of the filing of this action." See Complaint ¶ 248.

Subject to and without waiving its objections, Meta stands ready to meet and confer as to the scope of this Request. For the avoidance of doubt, Meta will not produce any documents in response to this Request unless and until the Parties have mutually agreed on the scope of production and subject matters implicated by this Request.

REQUEST FOR PRODUCTION NO. 53:

Average revenue per user from January 2007 through the present on a weekly basis:

A. Broken out by advertising revenue and non-advertising revenue; and

B. The above for each of Facebook's properties including but not limited to Facebook, Instagram, WhatsApp and Messenger.

RESPONSE TO REQUEST FOR PRODUCTION NO. 53:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this Request on the ground that it is overly broad, unduly burdensome, and disproportionate to the needs of the case, including without limitation because it seeks data created over a more than 14-year period on a "weekly" basis. Meta objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta additionally objects to this Request to the extent Consumer Plaintiffs seek information available to them from more convenient, less burdensome, or less expensive sources, including without limitation Meta's publicly filed quarterly, annual, and periodic reports. Meta also objects to this Request as unduly burdensome and not proportional to the needs of this case to the extent that it purports to require production of materials sought in other Requests (including without limitation Requests No. 8 and No. 9 of Advertiser Plaintiffs' First Set of Requests for Production). Meta further objects to this Request to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity. Meta also objects to this Request as irrelevant, including without limitation to the extent that it seeks data for properties other than Facebook, when Users proposed putative class is defined as "All

persons in the United States who maintained a Facebook profile at any point from 2007 up to the date of the filing of this action." See Complaint ¶ 248.

Subject to and without waiving its objections, Meta stands ready to meet and confer as to the scope of this Request. For the avoidance of doubt, Meta will not produce any documents in response to this Request unless and until the Parties have mutually agreed on the scope of production and subject matters implicated by this Request.

REQUEST FOR PRODUCTION NO. 54:

Total revenue from and number of ads served through Facebook Advertising Network on non-Facebook properties for 2014 through the present on a weekly basis.

RESPONSE TO REQUEST FOR PRODUCTION NO. 54:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this Request on the ground that it is overly broad, unduly burdensome, and disproportionate to the needs of the case, including without limitation because it seeks data created over a more than 14-year period on a "weekly" basis. Meta objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta further objects to this Request to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity. Meta further objects to this request as vague and ambiguous, including without limitation to the extent it relies on the terms "total revenue" and "number of ads," which are undefined and subject to more than one meaning. Meta further objects to this Request to the extent it refers to "Facebook Advertising Network," which does not exist. Meta will interpret this request as seeking information related to the Meta Audience Network (formerly known as the Facebook Audience Network).

Subject to and without waiving its objections, Meta will produce data for Audience Network by month and year for the time period January 2014 through October 2021 sufficient to show the Company's advertising revenue (in dollars) in the United States.

REQUEST FOR PRODUCTION NO. 55:

Structured data for an anonymized sample of non-Facebook users in the United States of the following information on a daily basis:

A. Database ID;

B. Non-user characteristics, such as gender and age;

C. Non-user geographic information;

D. Date;

E. All information about the non-user's on- and off-Facebook activity, including sites or types of sites visited, purchases made, affinity ("Like" button) or other tracking information, and user characteristics inferred or categorizations defined based on off-Facebook activity;

F. Number of ads served to the non-user by Facebook during their off-Facebook activity;

G. Number of ads served by Facebook to the user based on their Facebook activity;

H. Number of ads served by Facebook to the user based on their off-Facebook activity;

I. Device category (mobile, tablets, PC);

J. Device type (e.g., iPhone, Android);

K. All data about the non-user shared with any third party, including but not limited to app developers, including the content of the data and the identity of the third party; and

L. For each non-user in the sample, the data in this specification should be provided in raw form and in summary form by applying the tools and methods that Facebook uses in the ordinary course of business to summarize the data that it collects on individual non-users.

RESPONSE TO REQUEST FOR PRODUCTION NO. 55:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this Request as irrelevant to the extent it seeks data and information regarding "non-Facebook users," as Plaintiffs' purported class is comprised solely of Facebook users and any data that Meta may or may not maintain regarding non-Facebook users is not relevant

to any claim or defense in this action. Meta further objects to this Request on the grounds that it is overly broad, unduly burdensome, and not proportional to the needs of the case, including without limitation because this Request seeks more than 16 categories of information on a "daily basis" for a 14-year time period, including without limitation requests for "all information about the non-user's on- and off-Facebook activity" and "all data about the non-user shared with any third party." Meta additionally objects to this Request as vague and ambiguous, including without limitation to the extent it relies on the terms "non-Facebook users," "geographic information," "activity," "based on," "on- and off-Facebook activity," "tracking information," "non-user characteristics," "Database ID," "number of ads,"and "structured data," "inferred," "raw form," "summary form," "tools and methods" and "shared" each of which is undefined and susceptible to more than one meaning. Meta additionally objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta further objects to this Request to the extent it seeks the discovery of documents that are protected from disclosure by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity.

Subject to and without waiving its objections, Meta stands ready to meet and confer as to the scope of this Request. For the avoidance of doubt, Meta will not produce any documents in response to this Request unless and until the Parties have mutually agreed on the scope of production and subject matters implicated by this Request.

REQUEST FOR PRODUCTION NO. 56:

Structured data for an anonymized sample of users in the Consumer class and advertisements served to those users on both Facebook and on Facebook Advertising Network sites, on a daily basis, sufficient to identify:

A. Identity of the advertiser;

B. Internet location where advertisement was served (URL and any other available description or categorization);

C. All characteristics identified to the advertiser for the purpose of selling the advertisement, including but not limited to demographic information, location, social connections, Facebook group memberships, media viewed, or previous purchases;

D. The price paid by the advertiser for showing the ad to the user, including but not limited to per-impression rates, click-throughs or purchase bonuses, or per-campaign fees;

E. Whether any of the bidders knew the specific identity of the user, and if so whether the bidder provided the identity to Facebook or whether the bidder determined the identity in whole or in part on the basis of information received from Facebook; and

F. Whether the user purchased the advertised product or service, and the name and price of the product or service if purchased, regardless of which site or app the item was purchased on, and any additional revenues Facebook received as a result.

RESPONSE TO REQUEST FOR PRODUCTION NO. 56:

Meta incorporates by reference its General Objections and its Objections to the Definitions and Instructions.

Meta objects to this Request on the ground that it is overly broad, unduly burdensome, and not proportional to the needs of the case, including without limitation because it broadly seeks data regarding "all characteristics identified to the advertiser for the purpose of selling the advertisement" without regard to relevance or proportionality. Meta further objects to this Request on the ground that it is overly broad, unduly burdensome, and not proportional to the needs of the case, including without limitation because it seeks structured data regarding all advertisements served to a sample of users during a more than 14-year period on a "daily" basis. Meta also objects to this Request as vague and ambiguous, including without limitation to the extent it relies on the terms "internet location," "demographic information," "location," "social connections," "media viewed," "previous purchases," "click-throughs or purchase bonuses," and "per-campaign fees," each of which is undefined and susceptible to more than one meaning. Meta additionally objects to this Request to the extent it seeks information that Meta does not maintain in its normal course of business. Meta further objects to this Request to the extent it seeks the discovery of documents

that are protected from disclosure by the attorney-client privilege, work-product doctrine, or other applicable privilege or immunity. Meta further objects to this Request to the extent it refers to "Facebook Advertising Network," which does not exist. Meta will interpret this request as seeking information related to the Meta Audience Network (formerly known as the Facebook Audience Network).

Subject to and without waiving its objections, Meta stands ready to meet and confer as to the scope of this Request. For the avoidance of doubt, Meta will not produce any documents in response to this Request unless and until the Parties have mutually agreed on the scope of production and subject matters implicated by this Request.

Dated: January 23, 2023

Respectfully submitted,

By: /s/ Molly M. Jennings

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Attorneys for Defendant Meta Platforms, Inc.

EXHIBIT 11

From: Jennings, Molly <Molly.Jennings@wilmerhale.com>
Sent: Wednesday, June 21, 2023 9:33 AM
To: Brantley Pepperman; Guiney, Noah S.; Claire Hausman; WH Facebook Private Antitrust Litigation Service List
Cc: QE Facebook Antitrust; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: Re: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

[EXTERNAL EMAIL from molly.jennings@wilmerhale.com]

Brant,

Meta has no obligation to respond to your lengthy list of substantive questions concerning documents it produced outside of formal discovery requests – particularly not questions as unfocused as "please explain how the data file should be interpreted" asked for the first time in the last week of fact discovery. Nonetheless, in the interest of avoiding a dispute, we plan to produce this week a series of written responses Meta provided to certain questions identified by the FTC in lieu of providing 30(b)(6) testimony concerning data produced to the FTC. We expect that they will be informative for Users.

As to your specific questions concerning the MINT portal data: queries to the MINT portal provide data for the previous two years. Querying the MINT portal as Users specifically requested produced the files we then produced to you. There is no data available in the MINT portal for Bebo, Diaspora, flip.com, Google+, or Orkut, which is why no files for those entities were produced.

Thanks,

Molly

From: Jennings, Molly <Molly.Jennings@wilmerhale.com>
Sent: Friday, June 16, 2023 9:42 PM
To: Brantley Pepperman <brantleypepperman@quinnemanuel.com>; Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com <facebook-consumer-leads@lists.locklaw.com>; FB_AdvertiserCounsel@scott-scott.com <FB_AdvertiserCounsel@scott-scott.com>
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

Brant,

Please see attached correspondence.

Thanks,

Molly

From: Brantley Pepperman <brantleypepperman@quinnemanuel.com>
Sent: Friday, June 16, 2023 4:27 PM
To: Jennings, Molly <Molly.Jennings@wilmerhale.com>; Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

EXTERNAL SENDER

Molly,

It has been 3 weeks since Consumers sent the below correspondence concerning Facebook's re-production of structured data from the FTC case. We do not believe we have received a response—please provide one.

Consumers have additional questions regarding the FTC data, which are contained in the attached letter. We ask that Facebook promptly provide responses to these questions as well.

Finally, we understand that Facebook was to this week complete its production of structured data to the FTC. Please confirm whether Facebook has done so, and when Facebook will make any such production(s) available to Consumers in this case.

Thanks,

Brant

Brantley I. Pepperman
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213-443-3000 Main Office Number
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brantleypepperman@quinnemanuel.com
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From: Brantley Pepperman
Sent: Friday, May 26, 2023 8:00 PM
To: Jennings, Molly <Molly.Jennings@wilmerhale.com>; Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

Molly,

Please see the attached correspondence regarding Facebook's re-productions of structured data from the FTC matter.

Thanks,

Brant

Brantley I. Pepperman
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From: Jennings, Molly <Molly.Jennings@wilmerhale.com>
Sent: Monday, May 22, 2023 12:37 PM
To: Brantley Pepperman <brantleypepperman@quinnemanuel.com>; Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

[EXTERNAL EMAIL from molly.jennings@wilmerhale.com]

Brant,

Following up on my email below, I understand the bulk of ComScore data was also included in our production on May 12, 2023, and can be found at PALM-017052204 through PALM-017052276.

Thanks,

Molly

From: Jennings, Molly
Sent: Monday, May 22, 2023 10:58 AM
To: Brantley Pepperman <brantleypepperman@quinnemanuel.com>; Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

Brant,

We understand that, in addition to data from ComScore and App Annie, the MINT Portal included Onavo data and Study data at various times. The bulk of the underlying App Annie, Onavo and Study data was included in the data production that we made on May 12, 2023:

- App Annie: PALM-017052316 through PALM-017052405
- Study: PALM-017052581 through PALM-017052632, and PALM-017052725 through PALM017052726
- Onavo: PALM-017052633 through PALM-017052720

We intend to produce the remaining data underlying the MINT Portal, including ComScore data, early next week. In addition, we have also queried the MINT Portal for the data requested for in your April 11 letter. We are actively reviewing and processing the data and intend to produce them shortly. We will provide a further update on timing when we have one.

Apart from the MINT data, next week's production will include additional structured data produced to the FTC this week. Also, we understand that Meta will make additional structured data productions to the FTC. We will reproduce that data to *Klein* plaintiffs on a rolling basis, and expect to have completed these additional productions by the end of next week.

Thanks,

Molly

From: Brantley Pepperman <brantleypepperman@quinnemanuel.com>
Sent: Thursday, May 18, 2023 4:08 PM
To: Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

EXTERNAL SENDER

Counsel,

I am again following up on Consumer Plaintiffs' requests regarding the MINT Portal. Our requests have now been pending for more than 3 months, and it has now been 5 weeks since our April 11 letter and 3 weeks since Facebook on April 27 committed to provide a response. Please provide a date certain by which Facebook will produce the requested data, files, and information.

Brant

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From: Brantley Pepperman
Sent: Wednesday, May 10, 2023 3:52 PM
To: Guiney, Noah S. <Noah.Guiney@wilmerhale.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

Noah,
We confirm. We understand, as the parties agreed, Facebook will produce the data on May 12.
We appreciate your confirmation that Facebook will separately follow up regarding the MINT Portal requests. Please provide a date certain by which Facebook will produce the requested data, files, and information. Our requests have been pending for nearly three months, and we have not received a response to our April 11 letter regarding the MINT Portal requests, despite Facebook's April 20 representations to the Court that Facebook "expects to respond in the near term" (Dkt. 533 at 7), and its April 27 agreement to provide a response as soon as possible.
Thanks,

Brant

Brantley I. Pepperman
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213-443-3000 Main Office Number
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From: Guiney, Noah S. <Noah.Guiney@wilmerhale.com>
Sent: Wednesday, May 10, 2023 11:23 AM
To: Brantley Pepperman <brantleypepperman@quinnemanuel.com>; Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

[EXTERNAL EMAIL from noah.guiney@wilmerhale.com]

Brant,

The structured data Meta has agreed to produce in this case will all be marked "Highly Confidential" pursuant to the Protective Order. Section 7.2(c) of the Protective Order requires that all experts sign a "Acknowledgment and Agreement to Be Bound" to the Order, included in the Protective Order as Exhibit A, before they can receive information designated "Highly Confidential."

Meta is willing to produce the structured data via hard drive to the addresses listed below (along with the letters concerning this data sent by Meta to the FTC and a cross-reference comparing the data's bates numbers in the FTC case with their bates numbers in *Klein*) so long as you confirm that all of the experts who will access the data have signed an Acknowledgment and Agreement to Be Bound. Please promptly provide such confirmation.

We will follow up on the MINT portal requests separately.

Best,
Noah

From: Brantley Pepperman <brantleypepperman@quinnemanuel.com>
Sent: Wednesday, May 10, 2023 8:59 AM
To: Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

EXTERNAL SENDER

Counsel,

I am following up on my below email. Please confirm that Facebook will produce the FTC structured data in the manner described in my below email (*i.e.*, by hard drive to the addresses listed below). Please also provide an update regarding Consumers' request for data from the MINT Portal and Facebook's response to that request.

Thanks.

Brant

Brantley I. Pepperman
Associate
Quinn Emanuel Urquhart & Sullivan, LLP
865 S. Figueroa Street, 10th Floor
Los Angeles, CA 90017
213-443-3561 Direct
213-443-3000 Main Office Number
213-443-3100 Fax
brantleypepperman@quinnemanuel.com
www.quinnemanuel.com

From: Brantley Pepperman
Sent: Thursday, May 4, 2023 12:51 PM
To: Claire Hausman <clairehausman@quinnemanuel.com>; WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com; FB_AdvertiserCounsel@scott-scott.com
Subject: RE: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

Counsel,

I write to follow-up on Consumer Plaintiffs' and Facebook's agreement regarding structured data. We understand that by May 12 Facebook will re-produce to Consumer Plaintiffs the structured data Facebook already produced in the *FTC* litigation, and then, on a rolling basis, re-produce to Consumer Plaintiffs any further structured data that Facebook produces in the *FTC* litigation. We also understand that Facebook's re-productions will include the production correspondence Facebook provided to the FTC describing the data, that the data will be re-produced to us in such a way that we are able to use the correspondence to interpret the data (*e.g.*, there will be a way to address any different Bates numbering for the data as between the *FTC* and *Klein* cases), and that if Facebook learns any data dictionaries were produced in the *FTC* case, Facebook will reproduce those data dictionaries to us as well.

So that we can promptly load the data after receiving it, we request that Facebook provide the data via hard drive and ask that Facebook make three copies. Please send the hard drives to the following addresses:

Legal Economics
Attn: Thor Sletten
1305 Westwood Ave.
Columbus, OK 43212

EconOne
Attn: Justin Waller
550 S. Hope St., Suite 800
Los Angeles, CA 90071

Bates White
Attn: Neil Gautam
20011 K Street NW, North Building, Suite 500
Washington, DC 20006

Separately, we understand that Facebook is looking into the requests contained in my April 11, 2023 letter regarding the MINT Portal. Please advise when we can expect a further update from Facebook regarding those MINT Portal items.

Thanks,

Brant

Brantley I. Pepperman
Associate
Quinn Emanuel Urquhart & Sullivan, LLP
865 S. Figueroa Street, 10th Floor
Los Angeles, CA 90017
213-443-3561 Direct
213-443-3000 Main Office Number
213-443-3100 Fax
brantleypepperman@quinnemanuel.com
www.quinnemanuel.com

From: Claire Hausman <clairehausman@quinnemanuel.com>
Sent: Wednesday, April 19, 2023 6:48 PM
To: WH Facebook Private Antitrust Litigation Service List <WHFacebookPrivateAntitrustLitigationServiceList@wilmerhale.com>
Cc: QE Facebook Antitrust <qefacebookantitrust@quinnemanuel.com>; facebook-consumer-leads@lists.locklaw.com
Subject: No. 3:20-cv-08570-JD, Klein v. Meta Platforms, Inc - structured data requests

Counsel,
On December 23, 2022, Consumers served their Fifth Set of Requests for Production to Facebook requesting various structured data. Four months later, Consumers have not received responsive structured data from Facebook. We look forward to resolving negotiations regarding these document requests as soon as possible. However, Facebook's delay in producing responsive data is affecting Consumers ability to prepare their expert case. In an attempt to address this situation without briefing it to the Court while the parties may still be able to resolve it on their own, Consumers request that Facebook re-produce in this case, the structured data that Facebook produced to the FTC in the *FTC* case currently pending before Judge Boasberg. Doing so imposes no burden on Facebook and may help resolve the parties' negotiations more quickly. Additionally, Consumers hope it will get them at least some of the data relevant to preparing their expert case more quickly. To the extent there is certain structured data produced in the *FTC* case that Facebook believes has no relevance in this case, we are willing to forgo its production if Facebook identifies the data it is withholding and we agree it is not relevant. Please let us know Facebook's response to this request by April 24.
Regards,
Claire

EXHIBIT 12

2020

Antitrust in Attention Markets: Objections and Responses

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ANTITRUST IN ATTENTION MARKETS: OBJECTIONS AND RESPONSES

John M. Newman*

The modern antitrust enterprise finds itself under attack. Critics complain that enforcement agencies have done nothing to stem an ever-rising tide of market concentration and corporate power. At the center of this critique lies Silicon Valley, home of a new generation of tech giants.

Actual examination of agency actions suggests that these recent criticisms are somewhat overblown. Antitrust agencies, particularly the Federal Trade Commission, have brought a surprising variety of cases involving nascent markets. But there does remain a gaping void in the enforcement record: attention markets, in which individuals pay attention to advertisements in exchange for access to desired products and services.

This symposium contribution contends that attention markets represent the largest sector of the modern economy to have gone unnoticed by antitrust regulators. If it is to fulfill its congressional mandate, the antitrust enterprise must begin paying attention to attention markets. A number of objections to this straightforward point have been raised, but each collapses under close scrutiny. This article catalogues and refutes each of those objections, and concludes with a call to action: the ongoing lack of enforcement in attention markets risks delegitimizing the entire antitrust project.

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* Associate Professor, University of Miami School of Law. Hayden T. Cherry provided excellent research assistance.

I. INTRODUCTION

Orthodox antitrust has attracted a great deal of critical attention in recent years, much of it prompted by the rise of a new generation of Silicon Valley giants. A number of commentators from across the political spectrum have aligned around the position that antitrust enforcers have done too little to protect competition in digital markets.[1] Many of these critiques imply that enforcers have done nothing at all.[2]

But U.S. enforcement agencies have, in fact, filed a surprising number and variety of actions in digital markets. The Federal Trade Commission ("FTC"), for example, challenged Nielsen's acquisition of Arbitron on the unusual grounds that the deal would have combined two "potential" competitors—neither firm had entered the relevant market, but (per the FTC's complaint) both were planning to do so in the near future.[3] The FTC also recently challenged CDK Global's proposed purchase of a nascent rival, Auto/Mate, alleging that the acquisition

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1. *See, e.g.*, Lina M. Khan, Note, *Amazon's Antitrust Paradox*, 126 YALE L.J. 710 (2017); Jonathan Tepper, *The Conservative Case for Antitrust*, AM. CONSERVATIVE (Jan. 28, 2019), https://www.theamericanconservative.com/articles/the-conservative-case-for-antitrust-jonathan-tepper////; *The Next Capitalist Revolution*, THE ECONOMIST, Nov. 15, 2018, at 13; Matt Stoller, *The Return of Monopoly*, NEW REPUB. (July 13, 2017), https://newrepublic.com/article/143595/return-monopoly-amazon-rise-business-tycoon-white-house-democrats-return-party-trust-busting-roots.

2. Matt Stoller, *The Return of Monopoly*, NEW REPUB. (July 13, 2017), https://newrepublic.com/article/143595/return-monopoly-amazon-rise-business-tycoon-white-house-democrats-return-party-trust-busting-roots; Jonathan Tepper, *The Conservative Case for Antitrust*, AM. CONSERVATIVE (Jan. 28, 2019), https://www.theamericanconservative.com/articles/the-conservative-case-for-antitrust-jonathan-tepper////.

3. Complaint at 3, *In re* Nielsen Holdings N.V., and Arbitron Inc., No. C-4439 (F.T.C. Feb. 24, 2014), https://www.ftc.gov/system/files/documents/cases/140228nielsenholdingscmpt.pdf.

would have combined an actual competitor with a nascent competitor.[4] Finally, the agencies have successfully challenged a number of deals involving digital markets (FanDuel-DraftKings, H&R Block-TaxAct, Bazaarvoice-PowerReviews[5]) under the more traditional theory that the transactions would have combined actual, head-to-head rivals.[6]

If enforcers have been at least somewhat active and successful in digital markets, what has provoked the recent outcry? Despite the commendable efforts that have been undertaken, a gaping void in enforcement remains. A massive subset of the digital economy—markets that involve attention capture and exchange—has escaped enforcement altogether. This article describes how and why antitrust appears to have failed in this area, emphasizes the growing importance of attention rivalry, identifies the most common objections to antitrust enforcement in attention markets, and responds to those objections. It concludes with a call to action: digital attention merchants[7] have enjoyed *de facto* immunity from antitrust laws for too long. Intervention is essential, not only on its own merits, but also to preserve, in troubled times, the ongoing legitimacy of the antitrust enterprise.

4. Complaint at 4, *In re* CDK Global, Inc., No. 9382 (F.T.C. Mar. 26, 2018), https://www.ftc.gov/system/files/documents/cases/docket_no_9382_cdk_automate_part_3_complaint_redacted_public_version_0.pdf.

5. John M. Newman, *Antitrust in Digital Markets*, 72 VAND. L. REV., 47 (forthcoming 2019) [hereinafter Newman, *Digital Markets*].

6. As to conduct, the DOJ also brought a high-profile case against Apple and several e-book publishers. *See* United States v. Apple, 791 F.3d 290, 321, 339 (2d Cir. 2015) (upholding the lower court's decision that the challenged conduct was *per se* illegal). And, although the case did not directly involve digital markets, the DOJ filed a complaint in 2010 against six Silicon Valley firms that had entered into a series of agreements not to poach each other's employees. *See* Press Release, U.S. Dep't of Justice, "Justice Department Requires Six High Tech Companies to Stop Entering into Anticompetitive Employee Solicitation Agreements" (Sept. 24, 2010), https://www.justice.gov/opa/pr/justice-department-requires-six-high-tech-companies-stop-entering-anticompetitive-employee. The relevant market(s) at issue were labor markets, not digital markets. *See* Complaint, United States v. Adobe Sys., Inc., No. 1:10-cv-01629, 2010 WL 11417874, at ¶ 14 (D.D.C., Sept. 24, 2010) (contrasting the defendants' conduct with what occurs "[i]n a well-functioning labor market"). The FTC opened, but subsequently closed in 2013, an investigation into Google's search-related practices. *The FTC Report on Google's Business Practices*, WALL ST. J. (Mar. 24, 2015), http://graphics.wsj.com/google-ftc-report/; FED. TRADE COMM'N, GOOGLE INC. (2013), https://www.ftc.gov/enforcement/cases-proceedings/closing-letters/google-inc.

7. This term appears to have been coined by TIM WU, THE ATTENTION MERCHANTS: THE EPIC SCRAMBLE TO GET INSIDE OUR HEADS (2016).

II. THE RISE (AND RISE) OF ATTENTION RIVALRY

It is increasingly well-accepted—by everyone from advertisers[8] to rhetoricians[9] to theologians[10]—that attention is valuable. The potential supply of attention is finite, limited by both the total number of humans and by our individual ability to focus on a given phenomenon.[11] Despite these upper bounds, in an information-poor environment, attention is relatively abundant; there is more than enough to go around.[12] Pre-digital society left humans hungry for ways to expend their abundant supply of attention.[13] So long as information remains scarce, attention remains abundant. And where attention is abundant, it will be of little interest to economics, concerned as that discipline is with the allocation of scarce resources. By extension, it will also be of little interest to modern antitrust law, a discipline heavily reliant on economic theories and concepts.

But a shift to an information-*rich* society tends to cause a corresponding shift to an attention-*scarce* society. Nobel Laureate Herbert Simon posited that "the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is . . . the attention of its recipients."[14] In point of fact, Simons' statement was not quite accurate. Humans constantly engage in a process of screening and filtering: first selecting a set of items to be processed and rejecting others from that set, before actually devoting our limited mental resources to actual processing.[15] Thus, a wealth of information will not *necessarily* cause a scarcity of attention. If humans are able to screen and reject enough of the stock of

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8. Who, in 2016, spent nearly $200 billion in the United States alone. *See Statistics & Facts on the U.S. Advertising Industry*, STATISTA, https://www.statista.com/topics/979/advertising-in-the-us/ (last visited Jan. 23, 2019).

9. *See, e.g.*, Richard A. Lanham, *The Economics of Attention*, 2 MICH. Q. REV. (Spring 1997).

10. *See, e.g.*, Jasper L. Tran, *The Right to Attention*, 91 IND. L.J. 1023, 1029 (2016) ("The most desired gift of love is not diamonds or roses or chocolate. It is focused attention.") (quoting RICK WARREN, THE PURPOSE DRIVEN LIFE 127 (2002)).

11. *See, e.g.*, Jasper L. Tran, *The Right to Attention*, 91 IND. L.J. 1023, 1031 (2016) ("Both time and attention are scarce commodities."). This author uses the term "phenomenon" here in a Kantian sense, to be distinguished from noemena.

12. *See* Josef Falkinger, Limited Attention as the Scarce Resource in an Information-Rich Economy, IZA Discussion Paper No. 1538, at 4-5 (Mar. 2005).

13. *See* DOUGLAS L. WILSON, HONOR'S VOICE: THE TRANSFORMATION OF ABRAHAM LINCOLN 105 (1999) (describing Lincoln's walking twenty miles each way to borrow and return books); Herbert A. Simon, *Designing Organizations for an Information-Rich World*, COMPUTERS, COMMUNICATIONS, AND THE PUBLIC INTEREST 44 (M. Greenberger ed. 1971) ("Our attitudes toward information reflect the culture of poverty. We were brought up on Abe Lincoln walking miles to borrow (and return!) a book and reading it by firelight.").

14. Simon, *supra* note 13, at 40.

15. *See* Falkinger, *supra* note 12, at 6.

information, our attention can (in theory) remain abundantly available for the actual processing of select pieces of information. But our screening and filtering ability, like the rest of our cognitive functions, is limited.[16] Once the available supply of information exceeds this natural upper bound, the inverse relationship between supply of information and supply of attention envisioned by Simons will hold true.[17]

Like other scarce resources, the marketplace value of a given unit of attention can fluctuate. Where the value of a resource increases, profit-seeking firms will compete more vigorously to capture that resource.[18] This dynamic is of obvious interest to the antitrust enterprise. Two factors in particular—greater scarcity and technological change—can tend to increase the value of attention over time, thereby incentivizing attention-seeking firms to compete more vigorously to acquire it.

A. The Scarcity of Attention

Attention has become relatively scarce. Firms require the attention of trading partners—they must be *perceived by* counterparties—in order to participate in markets at all.[19] The less attention is available, the more difficult it will be for a given firm to attract it. At the same time, the market value of a given unit of attention increases, because the overall supply of attention is finite.[20] Thus, increases in information will (*ceteris paribus*) increase the value of attention and the degree of attention rivalry.[21]

For an antitrust enterprise concerned with safeguarding competition, a vital question emerges: has an age of information abundance arrived, bringing with it the corollaries of heightened attention scarcity and attention rivalry?[22] If attention rivalry has become

16. Ioannis Lianos, Digital Value Chains and Capital Accumulation in 21st Century Digital Capitalism: A Legal Institutionalism Perspective and Implications for Competition Law, at 37-39 (unpublished manuscript) (on file with author).

17. *See generally* Herbert A. Simon, *Designing Organizations for an Information-Rich World*, COMPUTERS, COMMUNICATIONS, AND THE PUBLIC INTEREST 44 (M. Greenberger ed. 1971).

18. ROBERT S. PINDYCK & DANIEL L. RUBINFELD, MICROECONOMICS 21-25 (Sally Yagan et al. eds.,7th ed. 2012) (describing the fundamentals of microeconomics).

19. *Id.* at 7-8.

20. *See* Lianos, *supra* note 16, at 37-39.

21. This should be understood as a macro-level statement. As to a given product, increased information may or may not change where consumers direct their attention. For a thorough discussion of firm level efforts to attract consumers' attention, see Pedro Bordalo et al., *Competition for Attention*, 83 REV. ECON. STUDIES 481 (2016).

22. Of course, this is a somewhat simplified version of the relevant question(s). Concepts like "abundance" and "scarcity" are best understood not as binaries—it is naïve to speak of a resource as if it is, or is not, definitely "abundant" or "scarce"—but rather as relative terms. It is useful to speak of a resource as "abundant" in relation to a different resource, or to

a significant type of marketplace activity, the antitrust enterprise must at least consider whether it is now deserving of more institutional attention.

We might begin to answer this question by considering advances in information technology. For untold millennia, information was relatively scarce.[23] But the Internet—"the world's largest copying machine"[24]—is drastically lowering the marginal costs of reproducing and distributing information. Viewed through this lens, the convergence of digital computing and networking was perhaps the single most important event in the evolution of IT.[25] Prescient observers recognized early on that the digital firehose of information threatened to consume massive amounts of attention.[26]

To get a sense for the magnitude of the increase, we can consider two sources of information that commonly consume attention: creative content and advertisements. The supply of creative content available for consumption has increased exponentially in recent years. In 2012, Spotify launched its popular online music streaming service with an on demand library of some 15 million songs.[27] Just ten years earlier, acquiring a similar library would have cost each individual consumer at least $30 million, according to one estimate.[28] The quantity of audiovisual content available has similarly surged: users upload 400 hours of video content to YouTube each minute, and viewers collectively watch more than 1 billion hours of YouTube videos each day.[29] Similar

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the same resource at a different point in time. Thus, the relevant question is more accurately (but less compellingly) whether information has become *relatively* abundant, thereby causing attention to become *relatively* scarce—and attention competition to become *relatively* important. Even more narrowly, we ought to care about whether attention competition has become *important enough* that the antitrust enterprise ought to sit up and take notice.

23. *See generally* WU, *supra* note 7 (describing how the progression from print, to broadcast media, to personal computers and mobile phones eventually devoured nearly every available piece of human attention).

24. Lena Groeger, *Kevin Kelly's 6 Words for the Modern Internet*, WIRED (June 22, 2011), https://www.wired.com/2011/06/kevin-kellys-internet-words/.

25. *See* Damon C. Andrews & John M. Newman, *Personal Jurisdiction and Choice of Law in the Cloud*, 73 MD. L. REV. 313, 322 (2013) ("The importance of the dawn of the Network Era for content, communication, and now computing, cannot be overstated.").

26. *See, e.g.*, Ellen P. Goodman, *Media Policy Out of the Box: Content Abundance, Attention Scarcity, and the Failures of Digital Markets*, 19 BERKELEY TECH. L.J. 1389, 1467 (2004) (arguing that information abundance had already led to attention scarcity as early as 2004 and that the resulting overload was producing market failures in digital contexts); Today, *Flashback! The Internet in 1995*, YOUTUBE (June 13, 2014), https://www.youtube.com/watch?v=95-yZ-31j9A ("I have no desire to be a part of the Internet because I feel like I'm so inundated with information all the time that I . . . don't want more.").

27. Doug Gross, *Myspace Gains 1 Million Users, Touts More Music than Spotify*, CNN (Feb. 13, 2012, 11:14 AM), https://articles.cnn.com/2012-02-13/tech/tech_social-media_myspace-millionnew-users_1_myspace-specific-media-spotify?_s=PM:TECH.

28. John M. Newman, *Copyright Freeconomics*, 66 VAND. L. REV. 1409, 1438 (2013).

29. Kit Smith BRANDWATCH, *46 Fascinating and Incredible YouTube Statistics* (Jan. 4, 2019), https://www.brandwatch.com/blog/39-youtube-stats/.

examples abound: Open Library's collection of millions of zero-price e-books,[30] SSRN's open-access library of scholarly papers,[31] and so forth.

Supply of advertisements has similarly skyrocketed. In 2007, one market research firm estimated that city dwellers experienced 5,000 ads per day, a figure that had more than doubled over the preceding thirty years.[32] In 2015, a skeptical marketer attempted to count how many ads he "actually" experienced over the course of a single day—but quickly abandoned the experiment, exhausted, having counted 487 unique exposures before breakfast.[33]

B. Demand-Side Innovation

Changes in technology can also increase the value of a given unit of attention, thereby incentivizing more robust attention rivalry. Recent advances in the ability to target advertisements represent one such development. Advances in digital data collection, storage, and analysis have allowed firms to more narrowly—and effectively—deliver targeted advertisements to individuals. These advances have made ads "more effective at generating both clicks and conversions," i.e., at attracting users to click on ads and buy the advertised products.[34] This increased effectiveness has increased the value (to advertisers) of ad placements.[35] And the more valuable the resource, the harder firms will compete to possess it.[36]

This demand-side innovation has yielded a marked increase in competition for attention. A variety of symptoms suggest this conclusion. The total number of ads delivered to consumers has risen sharply.[37] In a process dubbed "ad creep," advertisements have advanced further and further into formerly ad-free environments and

30. Accessible Book, OPEN LIBRARY, http://openlibrary.org/subjects/accessible_book (last visited Oct. 30, 2018).

31. A platform on which this article is, in fact, available. *See* SSRN, https://www.ssrn.com/index.cfm/en/ (last visited Aug. 15, 2019).

32. Louise Story, *Anywhere the Eye Can See, It's Likely to See an Ad*, N.Y. TIMES (Jan. 15, 2007), https://www.nytimes.com/2007/01/15/business/media/15everywhere.html.

33. Ron Marshall, *How Many Ads Do You See in One Day?*, RED CROW MKTG. INC. (Sept. 10, 2015), https://www.redcrowmarketing.com/2015/09/10/many-ads-see-one-day/.

34. Rebecca Walker Reczek et al., *Targeted Ads Don't Just Make You More Likely to Buy They Can Change How You Think About Yourself*, HARV. BUS. REV. (Apr. 4, 2016), https://hbr.org/2016/04/targeted-ads-dont-just-make-you-more-likely-to-buy-they-can-change-how-you-think-about-yourself.

35. *See, e.g.*, Laurie Burkitt, *Behavioral Ads Offer a Windfall for Marketers, Publishers*, FORBES (Mar. 24, 2010), https://www.forbes.com/2010/03/24/behavioral-targeted-ads-advertising-ftc-privacy-cmo-network-ads.html#5bc77b2c6042.

36. *See, e.g.*, PINDYCK & RUBINFELD, *supra* note 18, at 8-9.

37. *See* Story, *supra* note 32, and accompanying text; *see* Marshall, *supra* note 33, and accompanying text.

spaces.[38] Entry and product launches in attention-centric markets appear to have risen in recent years. The number of mobile applications available on the Apple App Store, for example, rose from 800 to 2.2 million in under a decade; another 3.6 million are available via Google Play.[39]

Firms competing to attract investors regularly tout their power and ability to exploit attention. Facebook's COO, for example, once boasted to investors that the firm's control of multiple digital platforms facilitated its power over its users: "[we] can take targeting and the ability to target across Audience Network, Facebook, and Instagram and *drive people all the way down the funnel*."[40] Google's CEO similarly touted his firm's ability to attract users' attention in order to resell it to advertisers:

> Our proposition to marketers . . . is simple and is resonating . . . . Our mobile properties, like Search, YouTube, Maps, and Google Play are where people turn when they are actively interested in something . . . . They are super-attentive and engaged . . . . This matters for marketers because those . . . moments when people are actively interested and attentive are the perfect time for a brand to place their ads.[41]

These competitive efforts have paid off handsomely. The market value of firms whose primary source of revenue is attention has grown considerably in recent years—in fact, the combined value of Alphabet and Facebook alone was more than $1.3 trillion as of May 2018.[42]

III. ANATOMY OF AN ANTITRUST FAILURE

Attention plays an ever increasingly vital role in modern economies. Markets in which firms act as "attention merchants"—intermediaries that extract attention from natural persons to use internally or sell to third parties—have exploded in number, variety, and

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38. *See, e.g.*, MARK BARTHOLOMEW, ADCREEP: THE CASE AGAINST MODERN MARKETING (2017); MATTHEW B. CRAWFORD, THE WORLD BEYOND YOUR HEAD: ON BECOMING AN INDIVIDUAL IN AN AGE OF DISTRACTION (2016).

39. *Number of Apps Available in Leading App Stores as of 3rd Quarter 2018*, STATISTA, https://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/ (last visited Jan. 23, 2019).

40. Facebook, Inc., Second Quarter 2016 Results Conference Call, 18 (July 27, 2016), https://s21.q4cdn.com/399680738/files/doc_financials/2016/q2/FB-Q216-Earnings-Transcript.pdf (emphasis added).

41. Digital Commerce 360, *Googles advertising revenue jumps 18.1% in Q3* (Oct. 27, 2016), https://www.digitalcommerce360.com/2016/10/27/googles-advertising-revenue-jumps-181-q3/.

42. *The 100 Largest Companies in the World by Market Value in 2018*, STATISTA https://www.statista.com/statistics/263264/top-companies-in-the-world-by-market-value/ (last visited Jan. 23, 2019).

size. Industry insiders and defendant-friendly commentators frequently claim these nascent markets are naturally competitive and self-correcting, such that antitrust intervention is unnecessary.[43] But real-world evidence tends to undercut such claims.

Many digital markets exhibit highly concentrated structures, with a single dominant firm possessing a massive share.[44] These shares are often quite durable,[45] undercutting the oft-heard trope that "competition is just a click away" in digital markets.[46] Respected foreign enforcers, most notably within the EU, have identified instances of anticompetitive conduct in digital attention markets.[47]

43. *See, e.g.*, Geoffrey A. Manne & Joshua D. Wright, *Google and the Limits of Antitrust: The Case Against the Case Against Google*, 34 HARV. J. L. & PUB. POL'Y 171, 195 (2011) (quoting with approval a website's claim that "as Google so often asserts, . . . competition really is 'just a click away' for a significant number of users" (internal quotation marks omitted)); Richard A. Posner, *Antitrust in the New Economy*, 69 ANTITRUST L.J. 925, 940 (2001) (concluding that "the states [should be] stripped of their authority to bring antitrust suits"); Adam Kovacevich, *Google's Approach to Competition*, GOOGLE PUB. POL'Y BLOG (May 8, 2009), https://publicpolicy.googleblog.com/2009/05/googles-approach-to-competition.html ("Competition is just one click away.").

44. Various industry sources have identified Google as owning between 91% and 97% of the "search" or "search engine" market. *See Search Engine Market Share Worldwide: June 2017-June 2018*, STATCOUNTER, http://gs.statcounter.com/search-engine-market-share#monthly-201706-201806; David McLaughlin, *Forget Consumer Welfare. This Antitrust Movement Targets Power*, BLOOMBERG (Jan. 17, 2018) https://www.bloomberg.com/news/articles/2018-01-17/forget-consumer-welfare-this-antitrust-movement-targets-power-instead (97.1%). By 2017, Amazon controlled 83% of U.S. e-book sales. *See* Newman, *Digital Markets*, *supra* note 5, at 7. As of February 2018, Facebook, Instagram, and Messenger represented the three largest mobile social-networking apps in the United States; all are owned by Facebook. *See Most Popular Mobile Social Networking Apps in the United States as of May 2018 by Monthly Users (in Millions)*, STATISTA, https://www.statista.com/statistics/248074/most-popular-us-social-networking-apps-ranked-by-audience/ (last visited Jan. 23, 2019). As of 2016, Google's Android represented 87.5% of all smartphone OSs being used worldwide. *See* Arjun Kharpal, *Google Android Hits Market Share Record with Nearly 9 in Every 10 Smartphones Using It*, CNBC (Nov. 3, 2016), https://www.cnbc.com/2016/11/03/google-android-hits-market-share-record-with-nearly-9-in-every-10-smartphones-using-it.html. In the market for digital real-estate portals, Zillow Group self-professedly enjoys shares of 67% across all platforms and 78% of mobile users. *See* John M. Newman, *Complex Antitrust Harm in Platform Markets*, ANTITRUST CHRON. (May 2017) (identifying the FTC's unconditional clearance of the Zillow-Trulia acquisition as a likely false negative).

45. *See* Newman, *Digital Markets*, *supra* note 5, at 5.

46. *See* sources cited, *supra* note 43.

47. *See* Press Release, Bundeskartellamt, *Bundeskartellamt Forbids Facebook to Merge User Data from Various Sources*, (Feb. 7, 2019), https://www.bundeskartellamt.de/SharedDocs/Meldung/DE/Pressemitteilungen/2019/07_02_2019_Facebook.html;jsessionid=150293B9ECA12757335989A66E51A893.1_cid371?nn=3591568; Press Release, Eur. Comm'n, "Antitrust: Commission Fines Google € 4.34 Billion for Illegal Practices Regarding Android Mobile Devices to Strengthen Dominance of Google's Search Engine," July 18, 2018, http://europa.eu/rapid/press-release_IP-18-4581_en.htm [hereinafter EC, *Google Shopping*]; Press Release, *Eur. Comm'n, "Antitrust: Commission Fines Google € 2.42 Billion for Abusing Dominance as Search Engine by Giving*

Yet the U.S. antitrust enterprise has largely ignored competition for attention. The most frequently criticized non-actions—including the FTC's unconditional clearance of Facebook's acquisitions of Instagram and WhatsApp, as well as the FTC's closure of its Google investigation despite evidence of anticompetitive behavior[48]—all took place in the context of attention markets. The Department of Justice ("DOJ") has adopted a similarly hands-off approach, dating at least as far back as its wholesale failure to investigate attention-market harms during the broadcast-radio merger wave of the late 1990s.[49] To date, neither the FTC nor the Department of Justice ("DOJ") has taken significant action in a zero-price attention market. Against the backdrop of attention scarcity and increasing rivalry, their collective failure to act presents a puzzle.

A growing number of critics suggest that society at large lacks an adequate understanding of, account for, and ability to direct and regulate human attention.[50] To the extent that is true, perhaps it ought not to be surprising that antitrust doctrine and commentary are similarly deficient in this area. Though a small handful of antitrust scholars have recently begun to grapple with the importance of attention, it remains something of a "blind spot" for courts and enforcers.[51]

Moreover, as I have explained elsewhere, the historical development of modern antitrust law and economics is at least partly to blame.[52] During the mid-twentieth century, a group of economists developed a novel set of tools to be used for analyzing industrial organization.[53] The tools themselves were fairly simple—for example, the idea that the relationship between price and quantity in a given

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Illegal Advantage to Own Comparison Shopping Service," June 27, 2017, http://europa.eu/rapid/press-release_IP-17-1784_en.htm.

48. *See The FTC Report on Google's Business Practices*, WALL ST. J. (Mar. 24, 2015), http://graphics.wsj.com/google-ftc-report/.

49. *See* John M. Newman, *Antitrust in Zero-Price Markets: Foundations*, 164 U. PA. L. REV. 149, 190-92 (2015) [hereinafter Newman, *Foundations*].

50. *See, e.g.*, MATTHEW CRAWFORD, THE WORLD BEYOND YOUR HEAD: ON BECOMING AN INDIVIDUAL IN AN AGE OF DISTRACTION (2015); ASTRA TAYLOR, THE PEOPLE'S PLATFORM: TAKING BACK POWER AND CULTURE IN THE DIGITAL AGE (2014); Tim Wu, *As Technology Gets Better, Will Society Get Worse?*, NEW YORKER (Feb. 6, 2014), https://www.newyorker.com/tech/annals-of-technology/as-technology-gets-better-will-society-get-worse.

51. *See, e.g.*, Tim Wu, *Blind Spot: The Attention Economy and the Law*, ANTITRUST L.J. (forthcoming), https://scholarship.law.columbia.edu/cgi/viewcontent.cgi?article=3030&context=faculty_scholarship; John M. Newman, *Antitrust in Zero-Price Markets: Applications*, 94 WASH. U. L. REV. 149 (2016) [hereinafter Newman, *Applications*]; Newman, *Foundations*, *supra* note 49; David S. Evans, *The Economics of Attention Markets* (Oct. 31, 2017), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3044858.

52. *See* Newman, *Foundations*, *supra* note 49.

53. Newman, *Foundations*, *supra* note 49, at 196.

market can be described by a downward sloping demand curve.[54] Prices played such a central role in formulating and applying these tools that the resulting approach became known as "price theory."[55] This methodological dependence on prices naturally and inevitably led to a rather singular focus on price competition in actual investigations and litigation.[56] Yet many attention exchanges lack obvious prices.[57]

If attention were relatively abundant, this error would be relatively harmless. But the rapid increase in the supply of available information, coupled with demand-increasing innovations, has led to a society that increasingly appears to exhibit attention scarcity. As a result, competition for attention has intensified. The stakes have grown considerably higher. Nonetheless, there are those who argue vigorously against any antitrust interventions into attention markets. The following discussion identifies, then responds to, their arguments.

IV. ANTI-ENFORCEMENT OBJECTIONS AND RESPONSES

A small but growing number of scholars and commentators urge increased antitrust oversight of attention exchanges. Proponents of the defendant-friendly status quo have raised various explicit and implicit objections to these calls for increased enforcement. The following discussion identifies and responds to each of their objections.

A. "We Are Already Doing Enough."

The first group of objections centers on the notion that current enforcement practices and tools are sufficient to address potential harms in attention markets. Two arguments fall into this category. The first is that understanding the impact of Big Data on market structure and performance is enough to allay concerns regarding anticompetitive conduct in attention markets. The second is that assessing the potential for harm to innovation will adequately address the possibility of harm in attention markets. Both arguments are well intentioned, but both miss the forest for the trees.

1. Paying Attention to Big Data Is Sufficient.

Perhaps the single most striking aspect of competition in digital markets is the massive shift away from users paying for products with

54. Richard A. Posner, *The Chicago School of Antitrust Analysis*, 127 U. PA. L. REV. 925, 928 (1979).

55. *Id.*

56. *See* Newman, *Foundations*, *supra* note 49, at 196; Khan, *supra* note 1, at 720 ("[One] consequence of the shift away from structuralism was that consumer prices became the dominant metric for assessing competition.").

57. *See* Lianos, *supra* note 16.

fiat currency. Instead, we frequently pay with our personal information and attention to advertisements. Curiously, antitrust and competition analysts have had a great deal to say about information—but almost nothing to say about attention.

Much of the ongoing debate over the current state of antitrust policy has centered on the rise of so called "Big Data." Conferences,[58] symposia,[59] panel discussions,[60] client alerts,[61] and dozens of books and articles[62] all focus on data-related practices and their implications for antitrust law. Pro-interventionists point to Big Data as a crucial competitive advantage and barrier to entry;[63] the anti-enforcement crowd argues in response that data is nonrivalrous and that its collection and exploitation is generally efficient.[64] Despite this scholarly *sturm und drang*, it seems a foregone conclusion that Big Data will impact enforcement efforts—the question on the minds of many U.S.

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58. *See, e.g.*, Conference, *Antitrust, Privacy, and Big Data* (Feb. 3, 2015), https://www.concurrences.com/en/conferences/antitrust-privacy-big-data-82922.

59. *See, e.g.*, Symposium, *Privacy Regulation and Antitrust*, 20 GEO. MASON L. REV. (Jan. 17, 2013), http://georgemasonlawreview.org/archives/vol-20-no-4-summer-2013/.

60. *See, e.g.*, Conference, *2018 Antitrust and Competition Conference-Digital Platforms and Concentration* (Apr. 19-20, 2018), https://research.chicagobooth.edu/stigler/events/single-events/antitrust-competition-conference-digital-platforms-concentration.

61. *See, e.g.*, *Exploring the Contrasting Views About Antitrust and Big Data in the U.S. and E.U.*, HOGAN LOVELLS (Sept. 27, 2018), https://www.hoganlovells.com/en/publications/exploring-the-contrasting-views-about-antitrust-and-big-data-in-the-us-and-eu.

62. *See generally* MAURICE E. STUCKE & ALLEN P. GRUNES, BIG DATA AND COMPETITION POLICY (2016); Daniel L. Rubinfeld & Michal S. Gal, *Access Barriers to Big Data*, 59 ARIZ. L. REV. 339 (2017); Ramsi A. Woodcock, *Big Data, Price Discrimination, and Antitrust*, 68 HASTINGS L.J. 1317 (2017); Daniel Sokol & Roison Comerford, *Antitrust and Regulating Big Data*, 23 GEO. MASON L. REV. 1129 (2016); Inge Graef, *Market Definition and Market Power in Data: The Case of Online Platforms*, 38 WORLD COMPETITION: L. & ECON. REV. 473 (2015); Nathan Newman, *Search, Antitrust, and the Economics of the Control of User Data*, 31 YALE L.J. ON REG. 401 (2014); James C. Cooper, *Privacy and Antitrust: Underpants Gnomes, the First Amendment, and Subjectivity*, 20 GEO. MASON L. REV. 1129 (2013); Geoffrey A. Manne & Ben Sperry, *The Problems and Perils of Bootstrapping Privacy and Data into an Antitrust Framework*, CPI ANTITRUST CHRON. (May 2015); Maurice E. Stucke & Allen P. Grunes, *No Mistake About It: The Important Role of Antitrust in the Era of Big Data*, ANTITRUST SOURCE (Apr. 2015); Darren S. Tucker & Hill B. Wellford, *Big Mistakes Regarding Big Data*, ANTITRUST SOURCE (Dec. 2014); Jens Prufer & Christoph Schottmüller, *Competing with Big Data*, Feb. 16, 2017, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2918726; David A. Balto & Matthew Lane, *Monopolizing Water in a Tsunami: Finding Sensible Antitrust Rules for Big Data*, (Mar. 23, 2016), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2753249; Anja Lambrecht & Catherine E. Tucker, *Can Big Data Protect a Firm from Competition?*, (Dec. 18, 2015), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2705530; Andres V. Lerner, *The Role of 'Big Data' in Online Platform Competition*, (Aug. 27, 2014), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2482780.

63. *See* Stucke & Grunes, *supra* note 62, at 6-7.

64. *See* Manne & Sperry, *supra* note 62, at 8-11.

practitioners is not whether some jurisdiction will intervene, but rather "which jurisdiction will strike first?"[65] In somewhat typical fashion, this debate has to some degree overlooked the European Union, where regulators have already recognized that consumers frequently pay with their personal information,[66] that such data can be used for product improvements[67] and/or targeted advertising,[68] that the need to amass data can serve as a barrier to entry,[69] and that a monopolist might extract supracompetitive levels of personal information instead of raising prices to users.[70]

This outpouring of intellectual effort stands in stark contrast to the near total silence regarding attention. Only a tiny handful of legal scholars and economists have weighed in on the role antitrust ought to play in attention-centric markets.[71] Enforcement agencies have initiated no meaningful activity focused on attention rivalry. If a single panel (let alone conference) has been devoted to competition for attention, this author is not aware of it.

Comparing the relative amounts of attention that have been paid to these two aspects of competition suggests an implied objection to the entire notion of antitrust enforcement in attention markets. The Big Data crowd appears to believe that information, not attention, is far more important to competition analysis—that properly understanding data related business strategies is the key to a properly functioning digital antitrust enterprise. Consider one commentator's take on digital markets:

> The race to accumulate data is already on, and is currently headed by giants such as Google and Facebook and, in China, Baidu and

65. Teleconference, *Big Data Antitrust Risks Which Jurisdiction Will Strike First?*, AM. BAR ASS'N, (July 24, 2018) (describing a July 2018 panel discussion on "Big Data Antitrust Risks.").

66. EUROPEAN COMM'N, *The Relevant Product Markets, in Antitrust Procedure* 29 (June 27, 2017), http://ec.europa.eu/competition/antitrust/cases/dec_docs/39740/39740_14996_3.pdf ("[E]ven though users do not pay a monetary consideration for the use of general search services, they contribute to the monetization of the service by providing data with each query.").

67. *Id.*

68. *Id.* at ¶ 204, n.129.

69. *Id.* at ¶ 286.

70. *See, e.g.*, Bundeskartellamt, *supra* note 47.

71. Gieuseppe Colangelo & Mariateresa Maggiolino, *Data Protection in Attention Markets: Protecting Privacy Through Competition?*, 8 J. EUR. COMPETITION L. & PRAC. 363 (2017); Wu, *Blind Spot*, *supra* note 51; Newman, *Applications*, *supra* note 51; Newman, *Foundations*, *supra* note 49; David S. Evans, *The Economics of Attention Markets*, (Oct. 31, 2017), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3044858; David S. Evans, *Attention Rivalry Among Online Platforms*, (Jan. 2, 2013), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2195340.

> Tencent . . . . [M]any of these companies . . . capture our attention . . . , and then they resell our attention to advertisers. Yet their true business isn't merely selling ads. Rather, by capturing our attention they manage to accumulate immense amounts of data about us, which are worth more than any advertising revenue.[72]

Under this view, Big Data is the forest, and attention but a tree. Tech companies seek our attention only in order to better capture our data. Under this view, paying attention to attention markets would amount to a waste of time and resources.

But this view gets it all backwards: firms generally do not seek attention in order to acquire data—instead, they frequently seek data in order to acquire attention. Much of the recent uptick in demand for personal data represents what an economist would call "derived demand."[73] The Big Data crowd would have us focus on the derived demand, while ignoring the more fundamental market forces at play. Cooper amusingly compares their misguided vision to that of the "Underpants Gnomes" in an eponymous episode of the TV show *South Park*.[74] In the episode, the Gnomes hatch a plan to strike it rich. Step one of the plan is to steal civilians' underpants. Step two is—well, the Gnomes do not actually have a step two. But step *three* is profit! Big Data alarmists seem to envision a similar strategy on the part of Silicon Valley giants. Step one, collect data. Step two, _______? Step three, profit![75]

In the marketplace, personal data is primarily harvested for two reasons.[76] First, firms collect data to satiate advertisers' desire to deliver personalized ads.[77] Such ads are more effective than generalized ads at

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72. Yuval Noah Harari, *Why Technology Favors Tyranny*, THE ATLANTIC, (Oct. 2018), https://www.theatlantic.com/magazine/archive/2018/10/yuval-noah-harari-technology-tyranny/568330/.

73. For an example of a resource as to which demand is derived from demand for some other resource, consider urban residential land: buyers' demand for such land is derived from their demand for housing. *See, e.g.*, Richard F. Muth, *The Derived Demand for Urban Residential Land*, 8 URBAN STUDIES 243, 243 (1971) (considering urban residential land as a resource whose demand is derived from some other resource: buyers' demand for land is derived from their demand for housing).

74. James C. Cooper, *Privacy and Antitrust: Underpants Gnomes, the First Amendment, and Subjectivity*, 20 GEO. MASON L. REV. 1129, 1135 (2013).

75. *Id.*

76. There are scattered other uses, of course—data is valuable to many entities, including governments, financial institutions attempting to assess credit or insurance risk, and political parties.

77. *See* Cooper, *supra* note 74, at 1136 ("The publisher hopes to enhance its revenue by using the additional data to . . . sell[] more finely targeted ads."); *see also* Catherine E. Tucker, *The Economics of Advertising and Privacy*, 30 INT'L J. INDUS. ORG. 326 (2012) (discussing the attractiveness of personalization to advertisers); United States v. AT&T, Inc., 310 F. Supp. 3d 161, 181-83 (D.D.C. 2018), *aff'd*, 2019 WL 921544, No. 18-5214 (2d Cir. Feb. 26, 2019)

driving consumer behavior—as Facebook put it, driving us "all the way down the funnel."[78] As a result, such ads tend to be more valuable to advertisers. Here, the demand for personal data is obviously derived from the demand for attention to advertisements.

Second, firms collect data to improve the quality of their own products, a practice that dates back to the dawn of consumer research as an identifiable discipline in the early twentieth century.[79] To the extent a resulting quality increase allows a firm to charge higher prices for its product, this second use of data can be an end in itself. But if the firm employs the zero-price, ad-supported business model that is ubiquitous in business-to-consumer digital markets, then even this second use represents derived demand—it is derived from the incentive to attract more attention, again in order to sell more (or more valuable) ads.

To get a rough sense of just how much more substantial attention-seeking is than pure data-harvesting, one might examine the annual revenues of each industry's largest players. Acxiom, a data broker, is (or at least was at one time) generally regarded as having the largest commercial collection of consumer data in the world.[80] Its annual revenues during the 2017-18 fiscal year were just over $900 million.[81] While not inconsiderable, Acxiom's haul pales in comparison to Google's ad revenue in 2017, which totaled more than $95 *billion*,[82] a figure more than 100 times larger than Acxiom's. And, of course, much of Acxiom's income was from sales to attention-seeking advertisers—it, too, was spurred by demand for attention.[83]

Thus, we see that focusing exclusively—or even primarily—on data and privacy concerns is a mistake. It is as if antitrust analysts in the

(defendants' including, as a key part of claimed efficiencies, increased ability to target advertisements).

78. *See* Facebook, Inc., *supra* note 40.

79. As early as the 1950s, consumer research was identifiable as a distinct scholarly field, with about ten academic articles on the topic being published each year. James G. Helgeson et al., *Consumer Research: Some History, Trends, and Thoughts*, *in* HISTORICAL PERSPECTIVE IN CONSUMER RESEARCH: NATIONAL AND INTERNATIONAL PERSPECTIVES (Jagdish N. Sheth & Chin Tiong Tan eds., 1985).

80. Natasha Singer, *Mapping, and Sharing, the Consumer Genome*, N.Y. TIMES (June 16, 2012), https://www.nytimes.com/2012/06/17/technology/acxiom-the-quiet-giant-of-consumer-database-marketing.html.

81. *Acxiom Corp. (ACXM) SEC Filing 10-K Annual Report for the Fiscal Year Ending Saturday, Mar. 31, 2018*, LAST10K (May 25, 2018), https://www.last10k.com/sec-filings/acxm/0000733269-18-000016.htm.

82. *Google's Ad Revenue from 2001 to 2017 (in Billion U.S. Dollars)*, STATISTA, https://www.statista.com/statistics/266249/advertising-revenue-of-google/. Facebook raked in another $39.9 billion during the same period. *Facebook's Advertising Revenue Worldwide from 2009 to 2018 (in Million U.S. Dollars)*, STATISTA, https://www.statista.com/statistics/271258/facebooks-advertising-revenue-worldwide/.

83. *See* ACXIOM DATA FAQ, https://www.acxiom.com/about-us/privacy/acxiom-data-faq/ (last visited August 1, 2019).

1990s, confronted by the explosive rise of personal computers, had concluded that the most important facet of industry competition was mousepads. Focusing solely on mousepads, demand for which is derived from the demand for PCs, would have overlooked the forest for a tree. And it would have caused enforcers to overlook Microsoft's monopolistic conduct in the far more important desktop computer operating system market.[84] Likewise, focusing solely on data and privacy concerns would unavoidably lead to false negatives.

Moreover, the competitive dynamics surrounding data and privacy are, for lack of a better word, messy. It is not clear that consumers regularly exhibit noticeable negative responses to increased levels of data-harvesting or that a dominant market position will generally allow a firm to extract more data from a given user than a smaller rival employing a similar business model could extract.[85] Evidence is somewhat mixed regarding the relationships among firm size, market concentration, and data extraction.[86] Although certainly possible in theory, it is difficult to establish as an empirical matter that data overcharges are occurring due to lack of competition.[87] The same cannot be said for attention competition, where enforcers' failure to act has already caused clear, measurable welfare harms.[88]

2. Paying Attention to Innovation Is Not Sufficient.

Where once U.S. enforcers seemed to ignore attention markets entirely, they now employ a slightly more evolved approach. In the past, antitrust agencies often explicitly ignored the zero-price side of platform

84. *See generally* United States v. Microsoft Corp., 253 F.3d 34 (D.C. Cir. 2001).

85. *See generally* Patricia A. Norberg et al., *The Privacy Paradox: Personal Information Disclosure Intentions Versus Behaviors*, 41 J. CONSUMER AFFAIRS 100 (2007) (describing a widely discrepancy between stated and revealed preferences regarding privacy).

86. *Compare* Gregory Day & Abbey Stemler, *Supracompetitive Privacy*, 107 IOWA L. REV. (forthcoming 2019) (describing empirical findings indicating a positive correlation between market concentration and lax privacy practices), *with* Lorien Sabatino & Geza Sapi, *Online Privacy and Market Structure: Theory and Evidence* (DICE Discussion Papers 308, 2019) (presenting empirical data indicating that large firms tend to offer more robust privacy protections than small firms).

87. This is not to say that data is irrelevant to antitrust and competition law analyses; as noted above, data can serve as a significant barrier to entry, can be exchanged as currency (therefore bringing the relevant markets within the scope of the antitrust laws), etc. And the Bundeskartellamt's actions against Facebook (currently still at a preliminary stage) may prove informative. *See generally* Giuseppe Colangelo & Mariateresa Maggiolino, *Data Accumulation and the Privacy-Antitrust Interface: Insights from the Facebook Case for the EU and the U.S.* (STAN. L. SCH. & UNIV. OF VIENNA SCH. OF LAW. TTLF Working Paper No. 31/2018, 2018), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3125490.

88. Newman, *Foundations*, *supra* note 49, at 192-95; *see also* Maurice E. Stucke & Allen P. Grunes, *Why More Antitrust Immunity for the Media Is a Bad Idea*, 105 NW. U. L. REV. 1399, 1411-12 (2011).

business models altogether.[89] More recently, enforcers have begun embracing at least the possibility of harm in zero-price markets. Post-review statements suggest that the agencies now consider one type of harm—harm to innovation—when reviewing questionable deals involving zero-price markets. Thus, for example, the FTC cleared Zillow's acquisition of its largest rival, Trulia, because "there was insufficient evidence . . . that the combined company would have a reduced incentive to innovate . . . on the consumer side . . . of the platform."[90] Somewhat similarly, the DOJ cleared Expedia's $1.3 billion acquisition of Orbitz in part because "the online travel business is rapidly evolving."[91]

This is a welcome development. In fact, one might even conclude that the current approach is sufficient—that looking for harm to innovation is enough to avoid false positives. But the "innovation only" approach would be sufficient only if (1) regulators are readily able to identify mergers that will likely harm innovation, and (2) the set of mergers that will likely harm innovation is coextensive with the set of mergers that will cause other types of harm. Since the latter is presently unanswerable due to a lack of data, let us focus on the first.

Unfortunately, *ex ante* prediction of harm to innovation is quite difficult. Typical merger reviews and litigation center on structural market analysis, testimony from market participants (especially customers of the merging parties), and internal documents from the parties themselves. While each of these are useful means of analyzing the likelihood of overcharges or output reductions, they are unlikely to yield much useful evidence regarding harm to innovation for two reasons.

First, there is a lack of robust support for a structural approach to predicting innovation harms.[92] Courts and enforcers are quite willing to

89. *See* Newman, *Foundations*, *supra* note 49, at 188.

90. Zillow, Inc./Trulia, Inc., FTC File No. 141-0214, *Statement of Commissioner Ohlhausen, Commissioner Wright, and Commissioner McSweeny Concerning Zillow, Inc./Trulia, Inc.*, (Feb.19, 2015), https://www.ftc.gov/system/files/documents/public_statements/625671/150219zillowmko-jdw-tmstmt.pdf.

91. Press Release, U.S. DEP'T OF JUSTICE, *Justice Department Will Not Challenge Expedia's Acquisition of Orbitz,* (Sept. 16, 2015), https://www.justice.gov/opa/pr/justice-department-will-not-challenge-expedias-acquisition-orbitz.

92. *Compare, e.g.*, Philippe Aghion et al., *Competition and Innovation: An Inverted U Relationship*, IFS Working Papers No. 02/04, at 47 (2004), https://www.econstor.eu/bitstream/10419/71449/1/342482874.pdf (concluding that empirical evidence generally supports an inverted-*U*-shaped relationship between concentration and innovation), *with* Chiara Peroni & Ivete S. Gomes Ferreira, *Competition and Innovation in Luxembourg*, 12 J. IND. COMPETITION & TRADE 93 (2012) (describing empirical results that do not support the inverted-*U* theory of the concentration-innovation relationship).

presume anticompetitive coordinated effects based purely on structural evidence indicating high levels of market concentration.[93] But they see much more reticent to presume that, for example, a four-to-three merger will reduce incentives to innovate.

Second, customers may occasionally express concerns about harm to innovation, but those concerns will likely be rare and inchoate. Customer concerns (or lack thereof) lie at the core of many agency reviews—a lack of concern is frequently grounds for closing down an investigation.[94] But harm to innovation is likely not foremost in the minds of most customers, who tend to be more concerned with short-run price effects. And customers typically have much less information regarding pipeline innovations than they do about the prices they pay for current products. Thus, any R&D related concerns customers might express may often appear to be less than reliable.

As a result, enforcers are left to rely primarily on the merging parties' own documents. But such documents (which are often quite fruitful for other purposes) will almost never indicate a likelihood of harm to innovation. What CEO would try to pitch a proposed merger or acquisition to her board of directors by claiming that the deal would allow the surviving firm to "stop innovating"?

Without econometric data or structural presumptions, and without the types of real-world evidence that often-shed light on harmful effects, contemporary analysts are generally unlikely to identify harm to innovation as part of merger reviews. Of course, complaints challenging mergers may allege harm to innovation in addition to the more traditional theories of harm.[95] But the received wisdom is that such allegations do not lie at the core of agency decision making and instead reflect the typical "laundry list" approach to complaint drafting in the post-*Twombly* era.[96] Tellingly, enforcers have never challenged a merger in a zero-price market based on a standalone theory of harm to innovation.

If enforcers cannot readily predict harm to innovation, it should come as no surprise when agency investigations fail to conclude that

93. *See, e.g.*, United States v. H & R Block, Inc., 831 F. Supp. 2d 27 (2011).

94. *See, e.g.*, Adam Putz, *M&A 101: What Antitrust Law Means for Mergers and Acquisitions*, PITCHBOOK (June 13, 2018), https://pitchbook.com/news/articles/ma-101-what-antitrust-law-means-for-mergers-and-acquisitions ("What single factor more than any other will keep a transaction from securing antitrust clearance? Companies should seek to understand how their customers will view a potential transaction. Favorable customer views may help on the margins, but negative reactions will almost certainly raise concerns at the Agencies, and cause deeper investigations and increase the likelihood of a challenge.").

95. Complaint at 3, United States v. AT&T, Inc., 916 F.3d 1029 (D.C. Cir. 2019) (No. 1:17-cv-02511).

96. *See generally* Bell Atlantic Corp. v. Twombly, 550 U.S. 544 (2007) (heightening the pleading requirements for plaintiffs in federal courts).

such harm is likely to occur. And if enforcers do not look for other types of harm, it should come as no surprise when no deals are challenged. Focusing on harm to innovation is a step in the right direction—but focusing *exclusively* on harm to innovation is tantamount to a policy of non-enforcement.

It is also not sufficient to ask, as DOJ recently did, whether the merged firm would likely impose positive prices on what had formerly been a zero-price market.[97] Raising prices from zero to a positive sum is a singularly unattractive way for firms to exercise market power.[98]

Instead, the antitrust enterprise ought to begin looking for attention-cost increases, which are much more analogous to the traditional price and output effects that generally form the core of actual agency investigations and litigation. Post-merger, will the firm have an increased incentive and ability to display advertisements to consumers? To be clear, this is not the same as asking whether the post-merger firm will have an increased ability to *target* advertisements.[99] The proper question is whether combining two firms will increase the merged firm's ability to extract users' attention by eliminating a competitive constraint. From this perspective, Facebook's acquisition of Instagram (for example) may have been less benign than it must have appeared to the FTC at the time. As Facebook's COO put it, the deal allowed the merged firm to target users across platforms in order to "drive them all the way down the funnel."[100] Unlike harm to innovation, this type of overcharge based harm maps rather neatly onto the basic microeconomic graphs and models that underlie much of antitrust in practice. A monopolist or cartel can raise its "price" (which here takes the form of attention costs), thereby reducing output and harming welfare.[101] For the antitrust enterprise to become serious about attention markets, it must consider seriously the possibility and likelihood of attention-based harm.

B. "We Are Incapable of Doing More."

The second category of anti-enforcement objections reflects a more pessimistic view: current antitrust law and economics do not allow for

97. *See* Press Release, *supra* note 91 ("[W]e uncovered no evidence in our investigation that the merger is likely to result in new charges being imposed directly on consumers for using Expedia or Orbitz.").

98. *See* Newman, *Applications*, *supra* note 51, at 74-77 (describing the power of the "Zero-Price Effect" on consumers).

99. This was one of the arguments successfully made by AT&T and TimeWarner in defense of their merger. *See generally* Chris Sagers, "The Worst Opinion in Living Memory: AT&T/Time Warner and America's Broken Merger Law" (Mar. 27, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3346431.

100. Facebook, Inc., *supra* note 40, at 16.

101. *See* Newman, *Foundations*, *supra* note 49, at 174-75.

increased oversight of attention markets. One of the two primary objections that fall into this category is that, as markets are currently defined, all firms competing for attention participate in the same massive market and, as a result, all lack market power. The second is that the current antitrust toolkit is not supple enough for use in attention markets.

1. Attention Is (Only) a Medium of Exchange

It is not uncommon to encounter arguments that all attention-seeking firms compete with each other in one massive, fragmented market—and that, as a result, none of them should face antitrust liability.[102] In other words, because Google, Facebook, CNN, Fox News, and the Dallas Cowboys all compete to attract eyeballs, they all must compete in the same relevant market.[103] The practical upshot is, yet again, non-enforcement of the antitrust laws, because each rival's individual share of this massive "market" would be miniscule.

Such arguments exhibit such obvious flaws that they almost do not deserve our attention. Yet the frequency with which they are made demands at least a cursory response. The error on display is fundamental: mistaking the medium of exchange for the metes and bounds of the market. One might just as well argue that movie theaters, grocery stores, nightclubs, and clothing designers all compete for money, and therefore must participate in the same relevant market. But no serious analyst would make such a claim.[104]

102. *See, e.g.*, David S. Evans, *Attention Rivalry Among Online Platforms* 1-2 (Univ. of Chi. Inst. for L. & Econ. Olin Res. Paper No. 627, 2013), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2195340 (arguing that "attention rivals" like search platforms, social networks, news providers, video hosts, etc., all "compete with each other for the limited time of consumers"); *Id.* at 3 (concluding that "[c]ompetition in fact appears to be quite robust 'in the market' "). As a policy matter, Evans urges a "strong presumption that attention seekers compete for procuring attention regardless of the products and services they offer for doing this." *Id.* This is supposedly warranted because "attention seekers are price takers in terms of what they pay to secure attention." *Id.*

103. Facebook arguably impliedly made a similar argument in response to the Bundeskartellamt's recent decision prohibiting certain of its data-collection practices. In a blog post disagreeing with the decision, Facebook included a graphic that (again, arguably) implied that Facebook competes with Twitter, LinkedIn, TicketMaster, Airbnb, TripAdvisor, Tinder, Yelp, Reddit, and others. *See* John Newman, *The Bundeskartellamt's Facebook Decision: Good, Bad, and Ugly*, REVUE CONCURRENTIALISTE (Feb. 11, 2019), https://leconcurrentialiste.com/2019/02/11/bundeskartellamt-facebook/ [hereinafter Newman, *Bundeskartellamt*].

104. Of course, defendants and defendant-friendly commentators often make claims that are only slightly less absurd. The Competitive Enterprise Institute, for example, argued recently that even a market definition as broad as "concerts" would be overly narrow—"[c]oncerts are one form of entertainment" that "compete[s] with movies, plays, ballgames, bars, restaurants, and countless other activities." Ryan Young, *Top Ten Antitrust Targets*, COMPETITIVE ENTER. INST. (Dec. 10, 2018), https://cei.org/blog/top-ten-antitrust-targets

In fact, the term "attention markets" itself—though useful shorthand—is something of a misnomer. The proper test for defining antitrust markets is what customers view as "reasonably interchangeable."[105] Thus, there may well be a market for "general internet search services," since to users social networking is likely not a reasonable substitute for search.[106] If so, we would not call this relevant market "attention to general internet search services," just as we would not refer to the beer market as the market for "money paid for beer."[107] The antitrust enterprise does not treat the medium of payment as a constitutive element of market definition. Consequently, the observation that "everyone competes for eyeballs" is a non-sequitur, irrelevant to the task of antitrust market definition.[108]

2. The Current Toolkit Is (Or at Least Can Be) Adequate

Defenders of the status quo—typically quick to promote the use of analytical tools like the SSNIP ("small but significant and non-transitory increase in price") test[109]—are surprisingly willing to admit the limitations built into such tools when arguing against antitrust enforcement in attention-based markets. The contemporary antitrust toolkit is largely organized around prices, a feature lacking in many modern markets.[110] Thus, the argument runs, our familiar tools are thus not up to the task currently required of them.

Confronted by such lacunae, analysts are faced with a choice: either attempt to update the toolkit or admit defeat and leave the novel problem unaddressed. Status quo defenders have chosen the latter, reasoning that we cannot go where our tools will not take us. But is simply throwing up one's hands in defeat a valid option? And, in any event, is the underlying descriptive claim—that antitrust lacks the tools to oversee attention-based markets—accurate?

As to whether simply accepting defeat is a viable option, it bears emphasizing that antitrust courts and enforcers have been tasked with a

("Not only are these [activities] fun, they also sap the strength of a possible antitrust case . . . .").

105. *See, e.g.*, United States v. Grinnell Corp., 384 U.S. 563, 571 (1966).

106. EC, *Google Shopping*, *supra* note 47.

107. *See, e.g.*, Complaint, United States v. Anheuser-Busch InBev SA/NV, No. 1:16-cv-01483, at 8 (D.D.C. July 20, 2016) ("Beer is a relevant product market . . . .").

108. Newman, *Bundeskartellamt*, *supra* note 103.

109. *See, e.g.*, Gregory J. Werden, *The Relevant Market: Possible and Productive*, ANTITRUST L.J. ONLINE (2014), https://www.americanbar.org/content/dam/aba/publishing/antitrust_law_journal/at_alj_werden.pdf.

110. Michal S. Gal & Daniel L. Rubinfeld, *The Hidden Costs of Free Goods: Implications for Antitrust Enforcement*, 80 ANTITRUST L.J. 521, 548-49 (2016) [hereinafter Gal, *Free Goods*].

broad congressional mandate: to protect "trade" and "commerce" in the United States.[111] Attention-based markets undoubtedly fall within this broad ambit.[112] Though they often lack obvious prices, they are nonetheless an increasingly important component of modern economies.[113] Like any other type of market, they present opportunities for the creation, enhancement, and abuse of market power—precisely the evils that antitrust laws are intended to remedy.[114] In the face of a congressional mandate to combat such evils, it is not permissible for enforcers to refuse their task on the grounds that their favorite tools are out of date.[115]

More fundamentally, the antitrust enterprise does not lack the requisite tools to oversee attention-based markets. Price-centric frameworks like the SSNIP test for market definition can sometimes be modified for use in zero-price markets.[116] Digital attention markets may be particularly viable candidates for SSNIP variants like the "SSNIC" or "SSNDQ" tests proposed by commentators.[117] Such markets greatly facilitate A/B testing (or "split testing"), in which two or more variants of a product or webpage are delivered to users at the same time for the purpose of testing user reactions.[118] One could easily envision the results of an A/B test focused on changes in advertising loads being used by antitrust analysts to define a relevant market.

Moreover, U.S. courts, including the United States Supreme Court, have long employed alternative factors, such as products' functional characteristics to good effect.[119] The flexibility offered by such

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111. *E.g.*, 15 U.S.C. § 1 ("Every contract, combination in the form of trust or otherwise, or conspiracy, in restraint of trade or commerce among the several States . . . is declared to be illegal.").

112. *See* Newman, *Foundations*, *supra* note 49, at 173-74.

113. *Id.*

114. *Id.*

115. *Cf., e.g.*, Morgan v. United States, 304 U.S. 1, 14 (1938) ("The vast expansion of . . . administrative regulation in response to the pressure of social needs is made possible under our system by adherence to the basic principle[] that the Legislature shall appropriately determine the standards of administrative action . . . ."). The author thanks Prof. David S. Romantz for direction to this line of authority.

116. Gal, *Free Goods*, *supra* note 110, at 548-49; Newman, *Applications*, *supra* note 51, at 66, 70.

117. Gal, *Free Goods*, *supra* note 110, at 548-49; Newman, *Applications*, *supra* note 51, at 66, 70. An alternative label for the SSNIC variant is "A-SSNIPS," proposed by Wu. *See* Wu, *supra* note 51, at 29.

118. *See* Ron Kohavi & Stefan Thomke, *The Surprising Power of Online Experiments*, HARV. BUS. L. REV. (Sept.-Oct. 2017) ("Today, Microsoft and several other leading companies—including Amazon, Booking.com, Facebook, and Google—each conduct more than 10,000 online controlled experiments annually, with many tests engaging millions of users.").

119. *See generally* United States v. Microsoft Corp., 253 F.3d 34 (D.C. Cir. 2001); *see generally* United States v. Grinnell Corp., 384 U.S. 563 (1966).

alternatives makes them much more robust in the face of ever-evolving business structures and strategies—sometimes, the old ways are the best.[120] Antitrust in general would benefit from moving beyond its current obsession with so called "quantitative" evidence. With the role of juries in antitrust trial having been greatly diminished, the old concern that laypersons would be misled by "smoking gun" documents has faded.[121] And quantitative data is perhaps even easier to massage and manipulate than real-world documents and testimony.[122] Numbers can be used to tell many stories. Anyone who has observed a modern antitrust trial has seen two highly credentialed economists manage to reach opposite conclusions—each somehow managing to favor the position of the client paying his astronomical fees—using the same underlying data.[123]

The objection that the antitrust toolkit is not supple enough to address attention markets is based on a faulty premise: that so called "quantitative" tools are the only one's modern analysts possess. Using real-world documents and testimony to analyze which firms a defendant actually competes with will quite often yield more accurate results than attempting to shoehorn modern digital markets into the narrow confines of hyper-technical, price-centric analytical tools (SSNIP-based market definition in particular). The antitrust toolkit is more robust than a handful of price-centric tests of recent invention and, at least in this context, dubious value.

C. "Doing More Would Do More Harm Than Good."

The third, and perhaps most serious, category of objections to antitrust oversight posits that increased scrutiny would do more harm than good. The first predicts that antitrust enforcement would chill capital market activity so badly that the resulting drag on the economy

120. *Cf.* SKYFALL (Eon Prods. 2012).

121. *See generally* Geoffrey A. Manne & E. Marcellus Williamson, *Hot Docs vs. Cold Economics: The Use and Misuse of Business Documents in Antitrust Enforcement and Adjudication*, 47 ARIZ. L. REV. 609 (2005).

122. *See, e.g.*, Jesse Eisinger & Justin Elliott, *These Professors Make More Than a Thousand Bucks an Hour Peddling Mega-Mergers*, PROPUBLICA (Nov. 16, 2016), https://www.propublica.org/article/these-professors-make-more-than-thousand-bucks-hour-peddling-mega-mergers. ("[A] ProPublica examination of several marquee deals found that economists sometimes salt away inconvenient data in footnotes and suppress negative findings, stretching the standards of intellectual honesty to promote their clients' interests.").

123. *See id.* ("'This is not the scientific method,' said Orley Shenfelter, a Princeton economist known for analyzing the effects of mergers . . . 'The answer is known in advance, either because you created what the client wanted or the client selected you as the most favorable from whatever group was considered.'"). The author uses the masculine pronoun in this context advisedly—virtually all of the highly paid economists who regularly testify in antitrust trials appear to be men.

would more than offset any gains to be had from increased competition. The second suggests that enforcement would prevent firms from achieving a particular type of efficiency, one that depends on leveraging established firms' expertise in production and distribution.

1. Enforcement Would Not Substantially Chill Capital Markets

It is not uncommon to encounter hand wringing over the possibility that antitrust enforcement in attention markets would chill capital investment activity.[124] But there is no evidence that such a chilling effect has ever occurred. Given the relatively toothless nature of modern U.S. antitrust law, particularly when it comes to attention markets, it seems highly unlikely that venture capitalists give serious thought to potential antitrust liability.[125]

If anything, it is the *lack* of antitrust enforcement that appears most likely to chill capital markets. The mere presence of Google or Facebook in a market can stifle innovation in that market.[126] Angel and seed investment activity in the United States has declined since 2015, both in terms of overall deal value and (more precipitously) number of deals closed.[127] Recent empirical research indicates that after Google vertically integrates into the market for an app that runs on its Android mobile OS, the developers of existing apps in that market reduce their efforts to innovate.[128] Even *The Economist*, long a bastion of undiluted *laissez faire* capitalism, has expressed concern over the "kill zones" that surround digital giants.[129]

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124. *See, e.g.*, Robert Litan, *Talk of Breaking Up 'Big Tech' Is Misguided, Premature*, THE HILL (Oct. 24, 2018), https://thehill.com/opinion/finance/412943-talk-of-breaking-up-big-tech-is-misguided-premature (arguing that venture capitalists "insist" on startups' having plans to be acquired by a large tech platform); *see also* Robert Litan & Hal Singer, *Are Google's Search Results Unfair or Deceptive Under Section 5 of the FTC Act?* (May 8, 2012), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2054751. Litan and Singer acknowledged that Google funded their paper. *Id.* at 1.

125. *See, e.g.*, Michael A. Carrier, *The Real Rule of Reason: Bridging the Disconnect*, 1999 B.Y.U. L. REV. 1265, 1348 (reporting that defendants won 96% of rule-of-reason cases over a ten-year period). Even criminal cartel prosecutions appear to be in steep decline, though that may reflect simply the normal ebb and flow of cartel work. *See* Kadhim Shubber, *US Antitrust Enforcement Falls to Slowest Rate Since 1970s*, FIN. TIMES (Nov. 27, 2018), https://www.ft.com/content/27a0a34e-f2a0-11e8-9623-d7f9881e729f.

126. *See, e.g.*, Newman, *Digital Markets*, *supra* note 5.

127. *See Panel 4: What Are the Goals of Antitrust? What Should They Be?*, MASONLEC https://vimeo.com/256528231 (video at 32:29) (remarks of Hal Singer).

128. Wen Wen & Feng Zhu, *Threat of Platform-Owner Entry and Complementor Responses: Evidence from the Mobile App Market* (HARV. BUS. SCH., Working Paper No. 18-036, at 19, 2017). The author thanks Hal Singer for the central insight, as well as the pointer to Wen and Zhu's work.

129. *American Tech Giants Are Making Life Tough for Startups*, THE ECONOMIST (June 2, 2018), https://www.economist.com/business/2018/06/02/american-tech-giants-are-making-life-tough-for-startups.

2. Incumbents Do Not Always Offer a Better Path to Market

One of the more interesting critiques of increased antitrust enforcement in attention markets—indeed, in any high-technology or dynamic market—is that it may prevent firms from achieving certain efficiencies. Essentially, the argument is that incumbent firms tend to be relatively poor at developing new products, but relatively good at developing innovative ways of producing or delivering products. Startups, on the other hand, tend to be good at product innovation—for many, that is their *raison d'être*—but relatively bad at actual production and distribution. Thus, an incumbent's acquisition of a startup may efficiently allow the incumbent to leverage its own unique advantages to capitalize on the startup's area of strength, while also representing a liquidity event for the startup's founders.[130] This is an intriguing insight, and one not yet well recognized by the antitrust community.[131]

It would, however, be a mistake to conclude from this that, as a general policy matter, antitrust should adopt a hands-off approach to attention markets. Many attention markets, at least those featuring online product delivery, do exhibit a degree of startup and acquisition activity. But it does not follow that, as to a given acquisition, allowing the dominant incumbent to be the acquirer is necessary to achieve process efficiencies or allow for entrepreneurial exit. As an initial matter, some other, non-dominant (yet established) firm might do so without any attendant risks of enhancing or entrenching market power. To the extent analysts should begin taking the entrepreneurial exit explanation into account, they must also begin considering the availability of less restrictive alternatives. But that is a narrow point; let us broaden the lens for a moment.

Antitrust discourse in general tends to lack a robust account of the incentives underlying mergers and acquisitions. Instead, the prevailing view is Manichean: mergers are generally "good" (undertaken to achieve productive efficiencies), but occasionally "bad" (intended to increase market power).[132] Entrepreneurial exit is only one of the many possible

130. *See* D. Daniel Sokol, *Vertical Mergers and Entrepreneurial Exit*, 70 FLA. L. REV. 1357, 1372-74 (2018).

131. *See id.* at 1371-72.

132. The descriptive claim that most mergers are procompetitive may well be incorrect. *See* Bruce A. Blonigen & Justin R. Pierce, *Mergers May Be Profitable, but Are They Good for the Economy?*, HARV. BUS. REV. (Nov. 15, 2016), https://hbr.org/2016/11/mergers-may-be-profitable-but-are-they-good-for-the-economy. The authors described the results of a recent study as follows:

> On average, we find that mergers do not have a discernible effect on productivity and efficiency. Specifically, we do not find evidence for plant-level productivity changes, nor do we find evidence for the consolidation of administrative activities that is often cited as a way in which mergers yield lower costs through economies

drivers for acquisition activity that have gone largely overlooked by the antitrust enterprise. The "hubris hypothesis" provides another: many acquisitions appear to be the result of managers' desire to engage in empire building[133] or simply pad their own pockets.[134] Such acquisitions have at their core a classic principal-agent problem.[135] Managers (agents of shareholders) are able to use mergers and acquisitions to enrich themselves at shareholders' expense.[136] Of course, where this results in an unjustifiably high acquisition price, one side effect is that the target firm's shareholders may benefit. As a result, the hubris hypothesis is not mutually exclusive of the entrepreneurial exit narrative: an acquirer's overbidding may naturally incentivize a startup's founder(s) to take the bid. But on the whole, a transaction driven by managerial hubris will tend to destroy, rather than create, societal value.

Moreover, it is quite possible that allowing incumbents to buy up rival startups and trading partners will cause dynamic harm in the medium to long run, even if such acquisitions yield the types of process efficiencies that underlie the entrepreneurial exit narrative. Startups often have unique firm cultures, managerial visions, and ways of approaching traditional market problems. They are, in antitrust parlance, particularly likely to play the role of "maverick" in an industry, continuing to disrupt the status quo even after their initial, breakthrough product innovations.[137] Allowing such valuable players to be subsumed into the relatively stale environs of an incumbent may cause society to lose out on what might be called "innovations along the way." To illustrate, consider an alternate universe in which Yahoo was allowed to acquire Google in the year 2000. It is impossible to know with absolute certainty what the world would look like today had Yahoo, instead of Google, been at the helm of Internet search for the past two decades—but most observers would likely agree that in such a world, society would almost certainly have missed out on more than a few innovations along the way.

> of scale. We also don't find evidence that merged firms are more likely to close down less-efficient plants. By contrast, we find substantial average increases in the amount that firms mark up prices over cost following a merger, ranging from 15% to over 50% . . . .

Id.

133. *See* CLAIRE HILL, BRIAN JM QUINN & STEVEN DAVIDOFF SOLOMON, MERGERS AND ACQUISITIONS: LAW, THEORY, AND PRACTICE 15 (2016).

134. *See* Yaniv Grinstein & Paul Hribar, *CEO Compensation and Incentives: Evidence from M&A Bonuses*, 73 J. FIN. ECON. 119, 119 (2004).

135. *Id.*

136. *Id.*

137. *See* U.S. DEP'T OF JUSTICE & FED. TRADE COMM'N, HORIZONTAL MERGER GUIDELINES, at 3-4 (2010).

Thus, while the antitrust community would do well to develop a more thorough understanding of capital markets and incentives, it would also be well advised to avoid pursuing an even more *laissez-faire* stance. In fact, to the extent a broad policy shift is warranted, it may well be in the opposite direction. We ought to recall the many empirical studies indicating that "mergers actually reduce the real profitability of acquired business units"[138] without creating value for acquirers or their shareholders.[139] The common assumption that most merger and acquisition activity is "procompetitive" may be out of step with reality. If anything, a more robust account of merger incentives may counsel in favor of more active enforcement, rather than an even more defendant-friendly version of the status quo.

V. CONCLUSION

Attention exchange has come to play an increasingly vital role in our economy, one that antitrust can ill afford to ignore. The current policy of non-enforcement has allowed massive societal harms to go unchecked; it has also left the entire antitrust enterprise vulnerable to critical attack. Focusing solely on the subset of economic activity that maps neatly onto price-centric models and tools is increasingly untenable. If antitrust is to play a meaningful role in the modern world—if it is to fulfill its congressional mandate to protect trade and commerce—the antitrust enterprise must begin to pay attention to attention markets.

138. Richard E. Caves, *Mergers, Takeovers, and Economic Efficiency*, 7 INT. J. IND. ORG. 151, 167 (1989).

139. *See, e.g.*, Ulrich Steger & Christopher Kummer, *Why Merger and Acquisition (M&A) Waves Reoccur-The Vicious Circle from Pressure to Failure*, 24 STRATEGIC MGMT. REV. 44 (2008) ("[M]ost M&As are considered to be unsuccessful.").

EXHIBIT 13

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1-6 Antitrust Law Developments 6B-3-c

Antitrust Law Developments > VOLUME I > CHAPTER 6 RELEVANT MARKET > B. Product Market Definition > 3. Economic Tests and Analyses

c. ***NATURAL EXPERIMENTS***

Analysis of ***natural experiments***, which is specifically mentioned in the *2010 Merger Guidelines*,[240] allows the comparison of certain key economic factors, such as prices in different geographic markets with different numbers of competitors or prices in a hypothetical market before and after an alleged anticompetitive act. Such comparisons, when conducted properly to control for temporal differences as well as differences in the geographic market, can allow economists to draw conclusions on the competitive impact of the behavior being studied and can be used to analyze market definition.[241]

In *FTC v. Staples, Inc.*,[242] the FTC successfully challenged the merger of two office superstore chains by comparing prices in geographic areas where the two chains were co-located to prices in areas where they were not co-located. This comparison constituted a natural experiment with the areas without co-location serving as a proxy for how the merged firm would behave. The court agreed that this analysis demonstrated that prices were lower in areas where Staples and Office Depot were co-located.

Another type of natural experiment is price correlation. The rationale for analyzing price correlation in defining a relevant market is that if two products are in the same product market, then their prices should tend to move together over time.[243] Even though commentators have questioned the relevance of

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240 2010MERGER GUIDELINES, *supra* note 20, §§ 2.12, 6.1.

241 *See, e.g.*, Mary Coleman & James Langenfeld, ***Natural Experiments***, *in* 1 ABA SECTION OF ANTITRUST LAW, ISSUES IN COMPETITION LAW AND POL'Y, 743-72 (2008).

242 *970 F. Supp. 1066 (D.D.C. 1997)*.

243 *United Food Mart v. Motiva Enters., 404 F. Supp. 2d 1344, 1348 (S.D. Fla. 2005)*.

price correlation as a tool for relevant market analysis, [244]some courts have found it to be informative but not dispositive. [245]

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[244] *See, e.g.*, Daniel L. Rubinfeld, *Econometric Issues in Antitrust Analysis*, J. INSTITUTIONAL & THEORETICAL ECON. 62-77 (2010); Patrick J. Coe & David Krause, *An Analysis of Price-Based Tests of Antitrust Market Delineation*, 4 J. COMPETITION L. & ECON. 983-1007 (Apr. 2008).

[245] *See, e.g.*, *United States v. Archer-Daniels-Midland Co., 866 F.2d 242, 246 (8th Cir. 1988)* (acknowledging price correlation between sugar and high fructose corn syrup (HFCS), but holding that it was not dispositive because government support for sugar created an artificial price differential between the products to the point where sugar did not act as a constraint on HFCS).

EXHIBIT 14

modern Industrial Organization

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the market including these substitutes was not large.
owever, that price substantially exceeded marginal
discussion, it was an error to include other wrapping
nition because they did not prevent the exercise of
the price of cellophane to competitive levels. If,
Pont had market power, the Court had investigated
vould raise the cellophane price, however, its market
appropriate.

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define markets.[14] It said: "The boundaries of such
ed by examining such practical indicia as industry or
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ates, 370 U.S. 294 (1962).

g economic markets, have occasionally attempted to define
ned within an economic market. Presumably competition be-
omic market is more intense if the two products also belong
on between *market* and *submarket* is not very useful, and we
give an economic definition of the term *submarket.*

step in defining markets; however, high correlations need not
in the same market. For example, dissimilar products made
rice correlations. Similarly, low correlations need not always
same market provided large quantity shifts accompany the
ne product rises, but the price of a good substitute does not,
oduct sharply declines.

The direct price elasticity—*not* the cross-elasticity of demand—determines market power. The **cross-elasticity of demand** is the percentage change in quantity demanded in response to a 1 percent change in another product's price. There is a lot of discussion in court decisions as to the importance of cross-elasticity of demand in defining markets. Courts often use the term loosely to indicate that products are substitutes. There is a relationship between cross-elasticity and direct elasticity, however. All else the same, the larger a cross-elasticity of demand, the larger in absolute value is the direct elasticity of demand.[17]

To intelligently discuss a cross-elasticity, one must specify whether it is the cross-elasticity of Product A with respect to the price of Product B or vice versa. Although these two different cross-elasticities are usually not distinguished in court decisions, they are not equal in general.[18] The relevant cross-elasticity of demand when the question is whether the market for Product A should include Product B is the cross-elasticity of demand for Product A with respect to the price of Product B.

The Extent of the Geographic Market. The geographic limit of a market is determined by answering the question of whether an increase in price in one location substantially affects the price in another. If so, then both locations are in the same market. The process of determining these limits proceeds along the same lines as discussed for the product market definition and involves similar reasoning. For example, consider the consumption of oranges in Chicago. Oranges are shipped to Chicago from outside the city limits. The geographic areas that ship to Chicago (or could profitably do so if price rose slightly) are in the same economic market as Chicago because they contain orange producers whose output significantly influences the price of oranges in Chicago. Notice that these same orange producers could also significantly affect the price of oranges in Milwaukee. Thus Milwaukee and Chicago would be in the same economic market, and the price of oranges in Chicago would generally be closely related to the price of oranges in Milwaukee.[19]

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[17]This result follows because the sum of the direct elasticity plus all cross-elasticities of demand equals 0. Let the cross-elasticity of demand of Product A with respect to the price of Product B be $\varepsilon_{AB} \equiv \frac{\partial Q_A}{\partial p_B}\frac{p_B}{Q_A}$, where Q_A is the (income-compensated) demand for A, and p_B is the price of B. Then, $0 = \varepsilon_{AA} + \sum_B \varepsilon_{AB}$, where ε_{AA} is the own (direct) price elasticity of demand for product A (Henderson and Quandt 1980, 31–3). The cross-elasticity of demand is positive for substitutes, and the direct price elasticity is negative. The direct elasticity can be large even if no individual cross-elasticity is large.

[18]From demand theory, $\frac{\partial Q_A}{\partial p_B} = \frac{\partial Q_B}{\partial p_A}$. This last relationship does not imply that the cross-elasticities of demand (defined in the previous footnote) ε_{AB} and ε_{BA} are equal (Henderson and Quandt 1980, 30).

[19]See Landes and Posner (1981), Scheffman and Spiller (1987), and Stigler and Sherwin (1985) for further analysis of market defi

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ment Science. Professor Besanko is a co-au
Economics of Strategy with David Dranove
Shanley, and Scott Schaefer.

TABLE 2.5 Cross-Price Elasticities of Demand for Selected Meat Products*

	Price of Beef	Price of Pork	Price of Chicken
Demand for beef	−0.65**	0.01***	0.20
Demand for pork	0.25	−0.45	0.16
Demand for chicken	0.12	0.20	−0.65

**Sources:* Table 1–4 in Daniel B. Suits, "Agriculture," Chapter 1 in *The Structure of American Industry*, 8th ed., Walter Adams and James Brock, eds. (Englewood Cliffs, NJ: Prentice-Hall, 1990).

**This is the price elasticity of demand for beef.

***This is the cross-price elasticity of demand for beef with respect to the price of pork.

demand substitutes Two goods related in such a way that if the price of one increases, demand for the other increases.

where P_j denotes the initial price of good j and Q_i denotes the initial quantity of good i demanded. Table 2.5 shows cross-price elasticities of demand for selected meat products.

Cross-price elasticities can be positive or negative. If $\epsilon_{Q_i,P_j} > 0$, a higher price for good j increases the demand for good i. In this case, goods i and j are demand substitutes. Table 2.5 shows examples of demand substitutes. For example, the fact

APPLICATION 2.4

How People Buy Cars: The Importance of Price

Table 2.6 presents estimates of the cross-price elasticities of demand for some of the makes of automobiles shown in Table 2.3. (The table contains the price elasticities of demand for these makes as well.) The table shows, for example, that the cross-price elasticity of demand for Ford Escort with respect to the price of a Nissan Sentra is 0.054, indicating that the demand for Ford Escorts goes up at a rate of 0.054 percent for each 1 percent increase in the price of a Nissan Sentra. Although all of the cross-price elasticities are fairly small, note that the cross-price elasticities between compact cars (Sentra, Escort) and luxury cars (Lexus LS400, BMW 735i) are zero or close to zero. This makes sense: Compacts and luxury cars are distinct market segments. Different people buy BMWs than buy Ford Escorts, so the demand for one should not be much affected by the price of the other. By contrast, the cross-price elasticities within the compact segment are relatively higher. This suggests that consumers within this segment view Sentras and Escorts as substitutes for one another.

TABLE 2.6 Cross-Price Elasticities of Demand for Selected Makes of Automobiles*

	Price of Sentra	Price of Escort	Price of LS400	Price of 735i
Demand for Sentra	−6.528**	0.078***	0.000	0.000
Demand for Escort	0.054	−6.031	0.001	0.000
Demand for LS400	0.000	0.001	−3.085	0.093
Demand for 735i	0.000	0.001	0.032	−3.515

**Sources:* Adapted from Table VI in S. Berry, J. Levinsohn, and A. Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 63 (July 1995): 841–890.

**This is the price elasticity of demand for a Sentra.

***This is the cross-price elasticity of demand for a Sentra with respect to the price of an Escort.

EXHIBIT 16

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Chapter 31

NATURAL EXPERIMENTS

Mary Coleman and James Langenfeld*

"Natural experiments" are frequently used in economic research, and some have advocated the increased use of such analyses in antitrust cases—including merger cases. A natural experiment systematically compares market outcomes between two markets, one being a control group (unaffected by the behavior at issue) and another that should be affected by the behavior. When properly done, natural experiments can provide important insights and allow economists to draw relevant conclusions. As in other economic analyses, natural experiments analyses are only useful, however, if (1) they reasonably fit the facts of the case, (2) employ sound economic methodologies that are based on reliable information, and (3) the inferences are accurately drawn from an appropriate economic model and other available evidence. These elements are at the heart of the criteria that courts are supposed to use to determine whether expert testimony should be heard under the *Daubert* test. This chapter describes the natural experiment methodology, explains how and why the *Daubert* criteria should apply to natural experiment analyses, and provides several examples of the use of these analyses.

1. Introduction

In evaluating antitrust liability or damages, economists often have either analyzed market structure and the nature of competition within a market or attempted to directly measure the impact of alleged anticompetitive acts. The former usually involves market definition based on the principles outlined in the 1992 *Horizontal Merger Guidelines*[1] and the calculation of market shares as a starting point in the analysis of market power. Directly measuring the impact of alleged anticompetitive acts often involves quantitative analysis of market outcomes before and after the alleged behavior, such as changes in price or output, while attempting to control for other market influences.

Economists have also used "benchmarks" or comparables in antitrust and other economic analyses to provide evidence on liability or damages for allegedly anticompetitive actions. These analyses usually compare the market outcomes from the alleged behavior to outcomes that are not affected by that behavior. The use of comparables is intended to control for many of the influences on a market that are not related to the actions at issue, and has been termed "natural experiment" analysis.[2] That

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* LECG, LLC, and LECG, LLC and Loyola University Chicago, respectively. The authors were involved in some of the cases discussed in this chapter, as indicated below. The authors thank Greg Werden, Luke Froeb, David Scheffman, Michael Vita, and Jessica Delbaum for their comments on an earlier version of this chapter.

1. U.S. DEP'T OF JUSTICE & FEDERAL TRADE COMM'N, HORIZONTAL MERGER GUIDELINES § 1 (1992) (with Apr. 8, 1997 revisions to Section 4 on efficiencies), *reprinted in* 4 Trade Reg. Rep. (CCH) ¶ 13,104.

2. As discussed below, other factors that could lead to higher prices still must be addressed in natural experiments, but a good natural experiment should in itself control for many of these other potential influences.

is, a natural experiment compares market outcomes associated with the firm or market of interest with those of other similar firms or markets that serve as a control group—unaffected by the behavior of interest. When properly done, natural experiments can provide important insights and allow economists to draw relevant conclusions.

For example, many economic analyses of alleged price fixing or of damages in antitrust and contract disputes may rely on benchmark or "natural experiment" analyses. In price-fixing cases, prices often have been studied to see if they increase at the time of the alleged agreement compared to the prices in unaffected geographic areas or for similar, but unaffected, products. If prices increase more in the area or products of interest than the benchmarks, then economists may infer that the excess price increase is due to the alleged agreement. In damages analyses, prices and sales are frequently compared to appropriate benchmarks to estimate what they likely would have been "but for" the challenged conduct.[3]

Interestingly, the term "natural experiments" has not, to date, had a generally accepted definition in the economic literature, with the term being used both more broadly and more narrowly than here. Some of the literature on natural experiments does not draw the distinction between direct measurement of effects, which does not rely on a control group, and the definition of natural experiment as used here, which does. For example, the definition applied in this chapter would consider a before-and-after study of the effects of a merger on prices to be a direct measurement if the variables used to control for other market influences on prices are specific to the merged firm (e.g., its input costs) or are general supply and demand factors. A natural experiment controls for these factors, at least in part, by using a control group, such as the contemporaneous performance of other similar firms or markets unaffected by the merger, or prior mergers in the same industry.

Natural experiment analysis in mergers only came to the forefront with *FTC v. Staples, Inc.*[4] In that case, the Federal Trade Commission (FTC) successfully challenged the proposed merger of Staples and Office Depot. An important part of the evidence the FTC put forward for both market definition and competitive effects arguably showed lower prices when the two merging firms competed in a geographic area, compared to areas or times when they did not.[5] These analyses are natural experiments, since they look at the impact of prior changes in, or contemporaneous differences in, the number and identity of competitors before the merger to draw

3. *See* ABA SECTION OF ANTITRUST LAW, PROVING ANTITRUST DAMAGES: LEGAL AND ECONOMIC ISSUES 36-39 (1996); SHANNON P. PRATT, ROBERT F. REILLY & ROBERT P. SCHWEIHS, VALUING A BUSINESS: THE ANALYSIS AND APPRAISAL OF CLOSELY HELD COMPANIES 869-70 (4th ed. 2000); ABA SECTION OF ANTITRUST LAW, ANTITRUST LAW DEVELOPMENTS 874-80 (5th ed. 2002); Robert H. Lande & James Langenfeld, *The Perfect Caper? Private Damages and the* Microsoft *Case*, 69 GEO. WASH. L. REV. 902 (2001).

4. 970 F. Supp. 1066 (D.D.C. 1997).

5. *See* Jonathan B. Baker, *Econometric Analysis in* FTC v. Staples, 18 J. PUB. POL'Y & MARKETING 11 (1999); Serdar Dalkir & Frederick R. Warren-Boulton, *Prices, Market Definition, and the Effects of Mergers: Staples-Office Depot*, *in* THE ANTITRUST REVOLUTION 52 (John E. Kwoka, Jr. & Lawrence J. White eds., 4th ed. 2004); Alan Frankel & James Langenfeld, *Sea-Change or Submarkets?* Federal Trade Commission v. Staples, Inc. and Office Depot, Inc., GLOBAL COMPETITION REV., June/July 1997, at 29.

conclusions about what would happen if the merger occurred. The FTC's evidence included company documents describing lower pricing in areas where more office superstores competed. For example, the FTC put forward the information shown in Figure 1 on differences in Staples' prices depending on the number of competitors in a geographic area and the identity of those competitors. In addition, econometric analyses estimated the impact of changes in the number and identity of office superstore competitors, and other office supply competitors, while attempting to control for important differences across the regions that could also influence prices. The FTC inferred that competition between the two potentially merging firms drove down Staples' prices in areas where they directly competed, and the merger would eliminate that competition and lead to higher prices.

The econometric studies put forward by the FTC's economic expert and defendant's economic expert came to differing results. The FTC's expert, Professor Orley Ashenfelter, found that prices were lower when Staples and Office Depot competed and when there were more office superstore competitors. The defendants' expert, Professor Jerry Hausman, found that the identity and number of office superstore competitors did not impact pricing. The court's decision granting a preliminary injunction against the merger appeared to rely most heavily on the company documents rather than the econometric testimony, but both sets of evidence were based on a natural experiment.

Many commentators have advocated the increased use of natural experiments to assess the potential competitive effects of mergers or other business practices that come

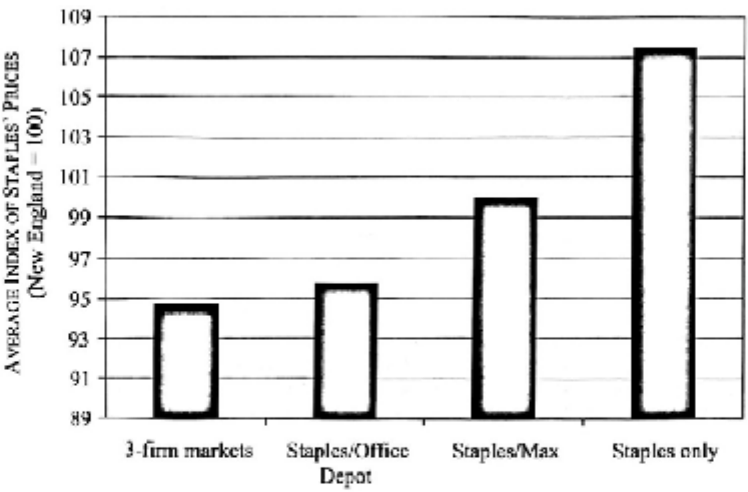

Figure 1.

Staples' average prices based on superstore competition, January 1997. Large office supplies sample.

under antitrust scrutiny.[6] Like other economic analyses, natural experiments analyses are only useful if they (1) reasonably fit the facts of the case, and (2) employ sound economic methodologies that are based on reliable information.[7] These elements are at the heart of the criteria that courts are supposed to use to determine whether expert testimony should be admitted under the *Daubert* test.[8] This chapter argues that these criteria can and should also apply to natural experiment analyses, whether done for litigation, regulatory analysis, or research.[9]

With regard to reasonably fitting the facts of the case, a natural experiment is valuable if the economic implications of the event and the market facts are sufficiently close to the behavior and market at issue. In *Staples*, the FTC was able to use the facts that the two merging parties competed in some areas and not in others, and that over time one or the other of the merging parties had entered into particular geographic areas. These "experiments" provided an approach to assessing the potential unilateral competitive effects from the merger. That is, did (1) the competition between Staples and Office Depot and (2) the number of office superstore competitors (including Office Max) affect pricing? These analyses had implications not only for competitive effects, but also market definition. To the extent that competition among office superstores had a significant impact on price, these natural experiments provided support that a relevant market was "office superstores."

In an evaluation of the potential impact of a prospective merger, natural experiments can be particularly useful, since the merger has not yet taken place and it is not possible to directly measure the merger's impact. In a consummated merger, one can in theory directly analyze the impact of the merger or use a natural experiment approach. The FTC took a natural experiment approach in the consummated Evanston-Highland Park hospital merger, because it chose to use the price changes of nonmerging hospitals as a benchmark, or control group, for determining the merger led to higher prices.[10]

It is not necessary that the experiment exactly mimic the behavior or market at issue, much as an economic model need not exactly mimic an industry to be of value. However, the further away the experiment is from the facts of the case at hand, the less

6. For instance, Luke Froeb, former Director of the Bureau of Economics at the FTC, has discussed the use of natural experiments to assess the competitive effects of vertical restraints. *See, e.g.*, Remarks of Luke Froeb, *The Use (and Abuse?) of Economic Evidence*, *in* CURRENT COMPETITION LAW 210-14 (Philip Marsden & Michael Hutchings eds., 2005).

7. See Bruce D. Meyer, *Natural and Quasi-Experiments in Economics*, 13 J. BUS. & ECON. STAT. 151 (1995), for a good discussion of the logic of the natural experiments approach as well as the problems that can arise with this approach. *See also* David Scheffman & Mary Coleman, *FTC Perspectives on Econometric Analyses in Antitrust Cases*, *in* ECONOMETRICS: LEGAL, PRACTICAL AND TECHNICAL ISSUES 115 (ABA Section of Antitrust Law 2005) (discussing best practices with regard to econometric analyses in antitrust cases).

8. Daubert v. Merrell Dow Pharms., 509 U.S. 579, 592-93, 595 (1993). See discussion *infra* Section 3.

9. Gregory Werden, Luke Froeb, and David Scheffman have advocated bringing *Daubert* discipline to another form of economic analysis—the use of simulation analyses in merger cases. *See* Gregory J. Werden, Luke M. Froeb & David T. Scheffman, *A* Daubert *Discipline for Merger Simulation*, ANTITRUST, Summer 2004, at 89.

10. *See* Evanston Nw. Healthcare Corp. and ENH Med. Group, Docket No. 9315 (FTC filed Feb. 10, 2004).

useful it is in assessing competitive effects. Moreover, one needs to check whether the results of the experiment are consistent with other economic analyses of the market at issue. If different aspects of the market are clearly inconsistent with the results of the natural experiment, the experiment also should be given much less weight.

With regard to sound economic methodologies and reliable data, it is important that the experiment be relatively "clean." As discussed below, natural experiments are not laboratory controlled experiments, because one cannot exactly recreate markets with and without the behavior at issue. Because natural experiments do not occur in a laboratory, many other factors are likely to change or be different in addition to the event that is the focus of the experiment. To make an inference as to whether the event caused a difference in outcomes, one may need to control for the other factors that may impact the outcomes. For example, in *Staples*, it was important to carefully control for factors other than the number and identity of office superstore competitors that could explain price differences across geographic areas and over time. These other factors included retailing costs (e.g., wages or land values) and demand (e.g., density of consumers or retailers purchasing office supplies).

In addition, the data or other information studied in the experiment, such as prices, must be appropriately and reliably measured. In *Staples*, prices were not higher for all products in regions with fewer superstores, and the prices of different products did not always fall after the entry of a new superstore. Accordingly, there were disagreements about how to appropriately weight the mix of products sold to determine the average prices in a particular geographic area at a particular time, which affected the conclusions that could be drawn from the experiments.

The remainder of this chapter describes in more detail natural experiment analysis as applied to antitrust. The next section explains exactly what constitutes a natural experiment, contrasting laboratory controlled experiments to natural experiments in antitrust analysis. Section 3 reviews some of the key factors one should consider in bringing *Daubert* discipline to natural experiments analysis. Section 4 provides a number of examples illustrating the strengths and weaknesses of natural experiments in antitrust analysis, with an emphasis on their use in prospective mergers.

2. What are natural experiments?

Experimental analysis is very common in scientific study. The general approach is first to create two groups: the "treatment" group and the "control" group. These groups are designed so that they have similar characteristics.[11] The major difference is that the treatment applies to one of the groups but not to the other. Once the treatment (an "event") occurs, the scientist compares relevant outcomes between the groups. Any significant differences in outcomes can then be attributed to the event.

For instance, a scientist studying the efficacy of a hypertension drug product will have two groups of patients with similar distributions of physical and medical characteristics. One group gets the drug being tested while the other gets a placebo.

11. Assignment to the groups often is random to ensure that the groups exhibit the same characteristics absent the experiment.

The blood pressure of each patient is recorded at the outset of the experiment and again after each group has taken their drug or placebo. If the group taking the hypertension drug has lowered its blood pressure on average relative to the other group, and this difference is statistically significant, then this test is an indication that the drug is efficacious.

Having a laboratory setting that can be used to test the issues raised in a particular antitrust case is rare. The substantial and growing body of research involving experimental economics is useful in understanding economic issues and the potential impact of various forms of competitive behavior at a general level.[12] However, using experimental analysis in a "laboratory" with volunteers as the decision makers may be of limited value in a specific antitrust case. The controlled conditions in the laboratory may be very different from those involved in a particular market, and such experiments would not involve the decisionmakers and companies involved in the market being analyzed.

Rather than use a laboratory setting, one can analyze events that have occurred in the industry, or a very similar industry, as a natural experiment. The premise is that an appropriate event could be used to approximate the competitive effects of a potential merger or other behavior being investigated. By reviewing the impact of the event on competitive outcomes (e.g., prices, quantities, or number of innovations), insights can be gained on the likely impact of the behavior at issue on competition.

Candidate events should include substantial, discrete changes in industry conditions over time or across geographic areas. A change over time that could be relevant for merger review would be a previous change in the industry structure, such as a previous merger. For the imposition of a vertical restraint, the change over time might involve a period when the restraint is in place versus a period when it is not.

Alternatively, the natural experiment might involve differences in industry conditions across geographic areas. In analyzing a merger, the presence of competitors might vary across regions, as in *Staples*, and one might analyze whether prices or other outcomes vary based on the number and identity of the competitors. For the imposition of a vertical restraint, one might compare outcomes in geographic areas where the restraint exists versus areas where it does not exist.[13]

Appropriate natural experiments can provide useful information on the nature of competition in the industry or the competitive effects of behavior similar to that at issue. Such analyses can be used instead of, or in addition to, other competitive effects analyses, such as simple market structure or models of competitive behavior such as "simulation analysis."[14] Analysis of market structure can provide useful evidence in evaluating competition. However, structure often is just the starting point for evaluating competition. Simulations use economic models to evaluate competition and predict the

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12. *See, e.g.*, Vernon L. Smith, *Economics in the Laboratory*, 8 J. ECON. PERSP. 113 (1994).

13. As discussed in more detail in the next section, it is important to assess whether the reasons for the different uses of restraints are endogenous or exogenous.

14. *See, e.g.*, Gregory J. Werden & Luke M. Froeb, *Simulation as an Alternative to Structural Merger Policy in Differentiated Products Industries*, *in* THE ECONOMICS OF THE ANTITRUST PROCESS 65 (Malcolm Coate & Andrew Kleit eds., 1996).

price effects of mergers.[15] However, the value of simulation models for evaluating and predicting competitive effects relies in large part on how well the models (e.g., Bertrand, Cournot, or other models of competition) fit the industry. Moreover, simulations make some significant assumptions that cannot be directly tested.

The type of competitive effects analysis that is most applicable in a particular matter will depend in large part on the information that is available, the ability to verify assumptions or control for differences, and how well each approach fits the economics of the case. Direct measures, natural experiments, and other indirect measures (such as structural analysis or economic modelling) can be complementary. For example, it may be that structural analysis or formal modeling is important for clearly interpreting the results of a natural experiment.

In addition to addressing the competitive effects of a particular action, natural experiments can be used to assess certain aspects of a structural analysis, such as entry or market definition. A review and analysis of past entry in a market may provide very useful information on the likely costs and success of future entry. For market definition, past experience with significant cost increases or supply disruptions might provide useful information on substitution patterns. Consider a case in which there are substantial imports and exports between regions, and it is important to determine whether particular countries or regions are relevant geographic markets. To determine whether customers would shift substantial purchases to suppliers outside a country or region, one might study exchange rate fluctuations or temporary local supply constraints (e.g., unanticipated factory shutdowns) to see if import and export flows shift in response to these exogenous changes.

Because natural experiments are not a direct measurement of the behavior at issue and an experiment almost never precisely mimics that behavior, one must make and test assumptions that underlie the natural experiments. Accordingly, natural experiments should be done in the context of the rest of the available evidence and should not be devoid of a consistent theory of competition and competitive harm. Any effects measured by a natural experiment must be tied to a reasonable explanation of why the behavior at issue would cause such effects, why it might be anticompetitive or procompetitive, and whether the full implications of the test present an economically consistent view of the industry.

3. Applying *Daubert* discipline to natural experiments analysis

Three Supreme Court decisions beginning with *Daubert v. Merrell Dow Pharmaceuticals*[16] and the 2000 revision of Rule 702 of the Federal Rules of Evidence[17]

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15. Simulations are based on key industry features, such as own- and cross-price elasticities, which are generally estimated from historical experience. *See, e.g.*, Daniel L. Rubinfeld & Roy Epstein, *Merger Simulation: A Simplified Approach with New Applications*, 69 ANTITRUST L.J. 883 (2001); *see also* Gregory J. Werden & Luke M. Froeb, *The Effects of Mergers in Differentiated Products Industries: Structural Merger Policy and the Logit Model*, 10 J. L. ECON. & ORG. 407 (1994).

16. 509 U.S. 579 (1993); Gen. Elec. Co. v. Joiner, 522 U.S. 136 (1997); Kumho Tire Co. v. Carmichael, 526 U.S. 137 (1997).

17. FED. R. EVID. 702.

have imposed strict standards on acceptable expert testimony.[18] When an expert invokes a natural experiment as support for an opinion on the competitive effects of a challenged practice or transaction, this testimony will be subject to these gatekeeping standards. If the testimony satisfies these standards, it then will be subject to testing through the normal adversarial process.[19]

In holding that the standard for admission of scientific expert testimony is governed by Rule 702 of the Federal Rules of Evidence, the *Daubert* Court required that the testimony be both reliable and relevant to the issues in the case.[20] In *Kumho Tire Co. v. Carmichael*,[21] the Court extended these requirements of reliability and relevancy as applicable to "testimony based on 'technical' and 'other specialized' knowledge."[22] In assessing the reliability of an expert's theory or technique, courts should consider all pertinent factors, including: (1) whether the expert's methodology "can be (and has been) tested," (2) whether it "has been subjected to peer review and publication," (3) its "known or potential rate of error . . . and the existence and maintenance of standards controlling the technique's operation," and (4) its "general acceptance" in the relevant scientific community.[23] In evaluating the utility of expert testimony, *Joiner* also states that "[a] court may conclude that there is simply too great an analytic gap between the data and the opinion proffered."[24]

Rule 702 now attempts to summarize the Court's teachings:

> If scientific, technical, or other specialized knowledge will assist the trier of fact to understand the evidence or to determine a fact in issue, a witness qualified as an expert by knowledge, skill, experience, training, or education, may testify thereto in the form of an opinion or otherwise, if (1) the testimony is based upon sufficient facts or data, (2) the testimony is the product of reliable principles and methods, and (3) the witness has applied the principles and methods reliably to the facts of the case.[25]

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18. *See* Dura Auto Sys. of Ind. v. CTC Corp., 285 F.3d 609, 614 (7th Cir. 2002); Schneider v. Fried, 320 F.3d 396, 404 (3d Cir. 2003); Lantec, Inc. v. Novell, Inc., 306 F.3d 1003, 1025 (10th Cir. 2002); Lust v. Merrell Dow Pharms., 89 F.3d 594, 598 (9th Cir. 1996); Amorgianos v. National R.R. Passenger Corp., 303 F.3d 256, 267 (2d Cir. 2002); Trouble v. Wet Seal, Inc., 179 F. Supp. 2d 291, 301 (S.D.N.Y. 2001). *See generally* Roger D. Blair & Jill Boylston Herndon, *The Implications of* Daubert *for Economic Evidence in Antitrust Cases*, 57 WASH. & LEE L. REV. 801 (2000); John E. Lopatka & William H. Page, *Economic Authority and the Limits of Expertise in Antitrust Cases*, 90 CORNELL L. REV. 617 (2005).
19. *See* FED. R. EVID. 702 advisory committee's note to the 2000 Amendments; Westberry v. Gislaved Gummi AB, 178 F.3d 257, 261 (4th Cir. 1999). *See generally* Blair & Boylston Herndon, *supra* note 18, at 802 ("*Daubert* challenges to the admissibility of the economic expert's testimony already are becoming routine in antitrust cases.").
20. *Daubert*, 509 U.S. at 588, 592.
21. 526 U.S. 137 (1999).
22. *Id.* at 141, 147-49, 152.
23. *Daubert*, 509 U.S. at 593-94; *Kumho Tire*, 526 U.S. at 150 ("*Daubert* makes clear that the factors it mentions do *not* constitute a 'definitive checklist or test.'").
24. Gen. Elec. Co. v. Joiner, 522 U.S. 136, 146 (1997).
25. FED. R. EVID. 702.

As some courts have concluded, Rule 702 imposes "three distinct substantive restrictions on the admission of expert testimony: qualifications, reliability, and fit."[26] Accordingly, we consider natural experiments in the context of the key *Daubert* and Rule 702 criteria in order to determine when such analyses are likely to be helpful and reliable. In discussing the important considerations in performing natural experiments below, it is assumed that the economist is qualified and, thus, only the other three elements listed in Rule 702 are discussed.

3.1. *Sufficient facts and data*

Having sufficiently reliable data is critical to all empirical economic analyses. Because a natural experiment compares outcomes across geographic areas, similar products, or the same products over time, a key challenge in conducting such an analysis is measuring these outcomes. As in any economic analysis, factors to consider include:

- What are the outcomes to be measured? Is the relevant measure price? Should output, quality, or innovation also be considered?
- How does one measure these outcomes? Determining the appropriate price and basket of products can be challenging.
- Are data available to measure these outcomes? How accurate are these data, and are they reliable? Are they available with sufficient frequency to conduct a reasonable analysis?

Natural experiment analysis may present more informational and data demands than structural or direct effects analyses. If the experiment involves comparing outcomes in different geographic markets, then reliable information and data on several geographic areas are needed—rather than just one market. If the analysis involves comparable products, then information and data also must be obtained for the other products. If the experiment analyzes the products at issue during an earlier period, then reliable data from that period must be available. If the data are seriously incomplete or unreliable, then analysis of even an appropriate natural experiment should carry little weight.

3.2. *Reliable principles and methods*

Does the experiment permit reasonable inferences about the behavior or market structure at issue? A natural experiment fits the facts of the case if it is likely to provide a good approximation of the competitive behavior at issue. Accordingly, one must determine how close the facts of the experiment are to the competitive issues and market of concern, and what types of conclusions can be drawn from the experiment. If one is trying to measure the impact of an alleged conspiracy on prices in one market compared to the prices in other geographic areas or for similar products, then the inference should be relatively straightforward. If there were a conspiracy, then prices should be higher in the market at issue compared to the control. Natural experiments may permit useful inferences even if the event in the natural experiment is different from the behavior or

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26. Elcock v. Kmart Corp., 233 F.3d 734, 741 (3d Cir. 2000); *see also* Club Car, Inc. v. Club Car (Quebec) Import, 362 F.3d 775, 780 (11th Cir. 2004).

market structure at issue. For example, in the Staples-Office Depot merger discussed above, the FTC analyzed the impact on price of the number of competitors across geographic areas and inferred that the merger's elimination of one office superstore would lead to higher prices. In some circumstances, the impact on price of a new entrant into a market also could provide evidence on how reducing the number of competitors likely would affect price.

Does the analysis use recognized economic concepts and statistical tools? As in all *Daubert* and Rule 702 evaluations, a natural experiment should use the appropriate economic concepts and statistical tools in devising and implementing the analysis.[27] In a natural experiment, the first step is to use the appropriate economic models to set up the tests for measuring the impact of the event on the relevant outcomes. An appropriate economic model captures the competitive process and structure of the market at issue and any comparable markets. Accordingly, one must evaluate whether the appropriate model for the market at issue is also appropriate for any comparable geographic markets or products, or appropriate for earlier time periods that might serve as a benchmark in the same industry. The relevant economic model accurately applied to the experiment should allow an economist to test whether, say, prices are higher with the alleged anticompetitive behavior, compared to where that behavior does not exist.

For example, if the products are relatively homogeneous and competition is primarily determined by price and output, a Cournot model may best reflect the markets' competitive process. In this situation, cost or capacity constraints should determine market shares in both the market at issue (absent an agreement to allocate customers) and any relevant benchmarks. If the products are differentiated, it may be more appropriate to use a Bertrand model where some products within a market are likely to be closer substitutes than others. In the latter case, determining relevant benchmarks may be more complex. If competition is primarily driven by innovation, then the model must focus on that and longer term market dynamics instead of short-term pricing. In this situation, the life cycle of comparable products may best provide a relevant benchmark.

The second step is choosing the appropriate methods for measuring the impact. These methods may involve a variety of analytic approaches. They can range from graphical analysis and bivariate comparisons of averages to sophisticated cross-section and time series econometric analyses (when sufficient reliable data are available). In general, more than one test should be used if possible.[28]

The applicability of experiments that use variations in market conditions (such as market structure) across geographic areas or over time depends on being able to show that the different outcomes are caused by the structure or behavior at issue. For instance, observed differences in market structure across different geographies may be "endogenous" or the result of other factors that also determined the observed differences in prices, profits, or output.[29] Consider the Cournot equilibrium condition of $(p - MC)/p = HHI/e$, where p is price, MC is marginal cost, HHI is the Herfindahl-Hirschman Index,

27. *See, e.g.*, Daniel L. Rubinfeld, *Econometrics in the Courtroom*, 85 COLUM. L. REV. 1048 (1985).

28. *See* discussion *infra* Section 3.3.

29. This is a common issue in cross-sectional studies.

and e is the elasticity of demand. Every variable in this equation may be endogenous in that underlying supply and demand factors will affect each of them. Thus, it may not be the market structure that impacts prices or profits, but rather other underlying factors. Economic theory (and the implicit or explicit economic model of competition that is being considered) will guide which variables are considered endogenous or exogenous.[30]

Whether endogeneity presents a significant problem for a natural experiment varies from case to case. The inferences drawn from a natural experiment require an understanding of the source of the change/difference in market structure and whether these differences are due to the variable of interest or the other underlying market conditions. A correctly crafted natural experiment in many instances should be able to separate the various influences by identifying the relationship between market structure and its underlying influences, correctly modeling those relationships, and employing the appropriate empirical technique.

When "exogenous" factors are the primary cause of market outcomes, it is simpler to infer that the event of interest caused differences in market outcomes being studied—rather than some other factor. Exogenous factors are not under the control of market participants, such as local regulatory restrictions, unexpected supply disruptions, or changes in demand. However, to some degree virtually all experiments may have potentially endogenous aspects. For example, a supply disruption could eliminate a competitor and also increase the marginal costs of the remaining competitors. In this case, use of the impact of the supply disruption to measure the impact on imports due to a merger (which would similarly eliminate an independent competitor) could cause the number of additional imports to be overstated because the cost-based increased prices of other competitors also would induce additional imports. This issue can be important both when comparing outcomes across geographic areas and over time. Nevertheless, even with some degree of endogeneity natural experiments can often provide reliable information, as long as the potential biases are recognized and not substantial.

Does the analysis control for other significant factors? Many industries exhibit significant changes in demand or cost over time or differences across geographic areas. Accordingly, an important element of natural experiments analyses is taking into account other factors that could influence outcomes in the control differently than the experimental group. When other factors prove to be important for the experiment, little inference may be made about whether the event "caused" the differences in outcomes under study without adequately controlling for these factors. In general, there are three approaches for controlling for other factors.

First, one can attempt to control for other factors within the context of the market being studied. For instance, consider an experiment that attempts to predict prices in the relevant market before and after a merger by studying the effects of a previous merger in the same industry. Changes in demand and supply conditions unrelated to the merger

30. *See, e.g.*, Peter C. Reiss & Frank A. Wolak, *Structural Econometric Modeling: Rationales and Examples from Industrial Organization*, *in* 6 HANDBOOK OF ECONOMETRICS (James Heckman & Edward Leamer eds., 2007).

also could have influenced prices in the previous merger. Such changes might include increases in cost or demand for the product, or supply disruptions. A regression might be estimated to measure the impact of the merger on prices while controlling for these other factors. The dependent variable (the variable whose behavior is to be explained) would be the prices before and after the previous merger. The independent variables (the variables that "explain" price movements) would include controls for costs, demand conditions (such as seasonal spikes in demand), supply disruptions, and an indicator variable for when that merger occurred. If the estimated effect of the merger variable is positive, statistically significant, and large enough to be economically significant, then this could provide evidence that the past merger resulted in higher prices—and the subsequent merger also likely would raise prices. A potential issue with this approach is that it requires obtaining information on the significant factors that can impact prices. Such data may not be readily available or of similar frequency to the outcomes data, so it may be difficult to isolate the impact of the event.

The second approach is to use a control group for the natural experiment that is not the specific market at issue. That is, as a benchmark, pick some geographic areas or a group of competitors in related industries that are similarly affected by the same supply and demand conditions as the experimental group, but that would not be affected by the competitive behavior at issue. One can compare, for example, the price changes for the experimental and benchmark groups before and after the event. If the experimental group has a significantly higher price change than the benchmark, this would be consistent with the event causing a price increase. Assuming the experiment meets the other requirements for reliability, one can use the results from the experiment in analyzing the likely impact of the actions under consideration.

Figures 2 and 3 provide a hypothetical example of using the control group approach. The experiment assesses the impact of a past merger or past imposition of a vertical restraint where the behavior might have an impact in one geographic area, but would not impact other areas that face the similar demand and supply conditions. The area potentially affected by the behavior is the Impact Area, and the other areas are Control Areas 1 through 5. The figures show the percentage price change before and after the event (i.e., the merger or the imposition of the vertical restraint) in each area. This percentage price change might be determined by comparing average prices before and after the event.

In Figure 2, the percentage change in price in the impact area is much greater than in the control areas, suggesting that the event had a significant unique impact. In Figure 3, the percentage change in price in the impact area is similar to changes in other areas, suggesting that the event did not result in a differential impact. Because the impact area and the control areas faced similar demand and supply conditions, and the only differing event was the behavior at issue, finding a differential price effect in the impact area suggests that the behavior increased prices. In contrast, finding no differential effect would suggest that the merger did not impact prices.

Finally, a third approach is to combine the techniques of the first two approaches. For example, one would use control or benchmark groups and also control for other factors that might impact the two groups differently.

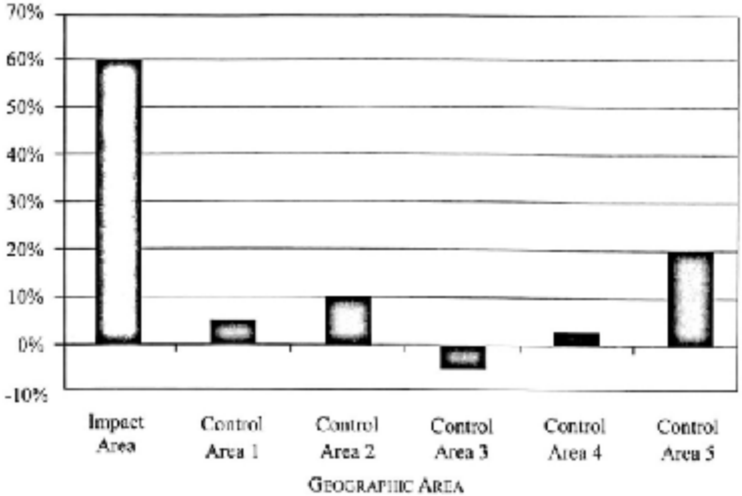

Figure 2.

Case 1—Weighted average percentage change in price, by geographic area.

3.3. *Applying the principles and methods reliably*

Does the experiment fit the facts of the case and are the inferences accurately drawn? The closer the facts and the nature of the experiment are to the issues and market of concern, the stronger is the inference that can be made from the results of the analysis.

For example, possible natural experiments for a prospective merger may involve previous acquisitions in the industry. Because the control is taken from the same industry, many potentially complicating influences from different geographies or products are eliminated—as long as the market has not changed substantially over time. However, the proposed merger could be different from past mergers and have an anticompetitive effect where the earlier mergers did not, or vice versa. For example, under a unilateral effects analysis, if prices increased as a result of past mergers with a combination of similar firms, then the experiment indicates that an additional merger in the industry likely would raise prices unless there were significant changes since the previous mergers. However, if prices did not go up, it would not necessarily imply that the merger at issue raises no concerns if, say, the market was less concentrated during the earlier merger.[31] Another potential experiment is to look at previous mergers in

31. Alternatively, a proposed merger could be less anticompetitive than a prior merger. Under a coordinated effects theory, a past merger could have lessened competition so much it would be unlikely that significant additional harm can be done by future mergers (i.e., more coordination is not likely). It might also be that a later merger could reduce the likelihood of coordination if the merged firm would be less likely to go along with the coordination. However, in the past, the agencies have

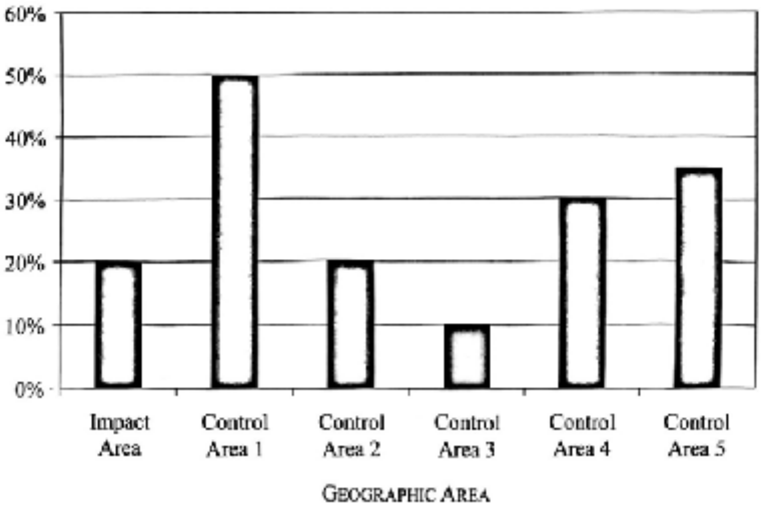

Figure 3.

Case 2—Weighted average percentage change in price, by geographic area.

other geographic areas that had a similar effect on market structure as the merger at issue. The usefulness of such an experiment depends on whether the conditions in the geographic areas and the nature of the mergers are similar enough that inferences can be made for the merger of concern.

With regard to market definition, substantial changes in industry conditions (such as cost increases or supply disruptions) might provide relevant information on substitution patterns. A significant change in industry conditions would likely involve large price changes, and one would expect to see substitution in response to large price changes. However, economic analysis of market definition generally involves assessing the potential substitution as the result of relatively small price changes. If little substitution occurred as the result of substantial change in conditions, then one would expect little substitution to occur at smaller price increases (unless the event was too short to trigger shifting). If substitution does result from a significant event, this result certainly indicates that substitution is possible. The substitution patterns resulting from significant changed market conditions can thus be informative, but it might be of limited value for assessing market definition based on substitution from relatively small price changes. Interestingly, recently in *FTC v. Arch Coal, Inc.*,[32] the court found that the

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sometimes challenged such subsequent mergers on the theory that loss of an additional competitor may make coordination more effective or less likely to break down.

32. 329 F. Supp. 2d 109, 121-22 (D.D.C. 2004).

defendants had shown that many customers frequently substitute between higher quality and lower quality coal, and that this was evidence supporting a market definition including both types of coal. The FTC argued that the defendants had not shown at what price such shifting occurred. The court concluded, however, that the FTC had the burden of proof with respect to market definition, and thus the burden was on the FTC to show that the observed shifting would not occur at modest price differences. The court found that the FTC had not met this burden.

The competitive dynamics of the industry must be very carefully interpreted when employing an endogenous natural experiment. Consider again the Staples-Office Depot merger in which the FTC examined the impact of differences in market structure across geographic areas. The natural experiment compared prices across the different geographic areas to determine whether (1) there were higher prices in more concentrated markets, indicating that higher concentration leads to higher prices; or (2) there were no observed differences in prices across regions, indicating changes in concentration (at least within the observed range) do not result in higher prices.

The inferences from such an experiment may not be valid if the differences in market structure are due to differences in aggregate demand in the areas—i.e., the differences in market structure are in part endogenous. In some areas, demand for the product may be relatively low. In these areas only a smaller number of competitors may be supported compared to other geographic areas where demand is higher and more competitors can be supported. In this case, supply and demand might equilibrate at similar price levels or margins—even though there are a different number of competitors—and a simple comparison of prices across geographic areas would imply the number of different competitors has no impact on competition. However, it would be difficult to make a strong inference from such an analysis that reducing the number of competitors in a high demand area would be unlikely to result in higher prices. One would have to effectively control for the impact of market size before any conclusions could be reached. A cleaner experiment could be one where regulatory restrictions that are less likely to be endogenous, such as certificate of need laws or zoning restrictions, result in fewer competitors regardless of the size of the market.[33]

Another example involves vertical restraints whose use varies across geographic areas (or over time). In some cases, the firm imposing the restraint may choose to have different policies in different geographic areas (or change its policy over time) while in other cases differences in local regulations may force these differences. The latter could be an exogenous reason for the difference in use, while the former would be in part an endogenous reason. To see why the former could raise problems when using an experiment to assess the effects of the vertical restraint, consider the following example. McDonald's owns some company operated stores but franchises most of its locations. McDonald's will want to franchise in locations where the franchisee's incentives are aligned with McDonald's for building the brand reputation and own stores in areas where the incentives are not aligned. This decision might differ by geographic area. Some geographic areas (such as cities or suburbs) may have substantial repeat business

33. One must also be careful to try to distinguish the effects of these restrictions on available supply versus the number of competitors.

at the same location, while other areas (such as stops along a highway) may have little repeat business at the location—but still have the potential for repeat business for the brand. In the first case, incentives may be aligned, as the franchise and McDonald's both benefit from repeat business from the same customers. In the second case, the incentives may not be aligned. Here the franchisee could free ride off McDonald's brand name and have little incentive to serve individual customers well because the franchisee will not likely see the same customer again. If so, one might see company-operated stores along highways but not in cities or suburbs. There may be no differences in quality or price for company-operated versus franchised locations by geographic area, because the more efficient structure for each area is used in that area. It would be inappropriate to infer there were no benefits from the vertical integration in this example, because such integration only occurs in the areas where it provides benefits to offset potential free-rider problems.

Experiments involving entry usually will be in part endogenous, but useful experiments still may exist. Firms choose to enter an industry or an area because they observe a profit opportunity—possibly because prices are above the long-run competitive levels. The higher prices could be because of lack of competition in the industry or because capacity is currently low relative to demand. In either case, entry could cause prices to fall from where they would have been without the entry, but both do not have the same implications for whether a reduction in the number of competitors will result in higher prices. If entry is in response to increasing demand, lower prices also could occur as the result of expansion by existing competitors. Thus, it may be difficult to distinguish between the impact on prices from an increase in capacity due to entry versus an increase in the number of competitors. Entry still may provide useful information as to the nature of interactions among competitors and the requirements for and profitability of entry. Entry analyses also may provide information on customer substitution patterns useful in addressing issues such as market definition. However, natural experiments on the effect of entry will be more reliable when there are ways to separate the effects of capacity increases from number of competitors, such as comparing areas where capacity has increased without increasing the number of competitors to other areas where both have increased.

Even where the reasons for the events are exogenous (e.g., as the result of local regulations), issues still can arise in distinguishing the effect of the event. It is possible that the exogenous events impact several factors that can affect market outcomes, including the one under concern. If so, distinguishing between impact from the different market conditions that are the focus of the experiment versus other market conditions may be difficult unless there are controls for the latter. For instance, some cities may have strict zoning restrictions for the building of new gasoline stations, while other cities might have fewer restrictions. This could result in fewer stations per capita in the former cities than in the latter cities and, thus, less capacity overall. Such regulation also might result in fewer competitors, because fewer firms find it worthwhile to invest in developing a brand or a network of stations. Both the reduced capacity generally and the fewer number of competitors due to the regulations could result in higher prices. Therefore distinguishing between these two effects may be difficult. As with the entry example, this might be overcome by controlling for capacity differences in the analysis.

Are the results robust and economically reasonable? For the results of a natural experiment to be economically sound, they should be "robust" when tested with different recognized approaches and data sets, and the results should be economically consistent with other aspects of the market and the theory of the case.

A natural experiment is robust if the results do not change significantly with economically reasonable changes in the analysis. That is, the results are similar when using different data sets, different possible measures of outcomes, different means of controlling for other factors, different economically sound analytical approaches, or different applicable estimating techniques. If not, reasonable questions may be raised about the reliability of the experiment. When the results are highly sensitive to modest and reasonable changes in data, assumptions, or analytical approaches, the natural experiment should be considered unreliable.

It also is important to consider whether the results are economically sensible. For example, is it plausible that observed differences in prices could be explained by the event under consideration?[34] Consider the case where the natural experiment involves comparing prices before and after the imposition of a vertical restraint. Suppose one finds that market prices increased by 20 percent. However, in the relevant market the firm imposing the restriction has only a 10 percent share, and other firms with larger shares do not use the restraints. It may not be plausible for a firm with such a small share to cause a market-wide price increase with its vertical practices. As a result, one would question whether the experiment was a "good" experiment. That is, have the effects been measured correctly, or has the relevant market been defined incorrectly?

Similarly, one should consider whether (1) the results are consistent with other aspects of the competitive situation in the market, and (2) the results are not consistent with potential procompetitive explanations of the outcomes. For instance, one might find not only that prices went up after a merger, but also that the merged firm's share increased or its overall unit sales increased. In general, output expansion would not be consistent with anticompetitive behavior. Rather than the merger having an anticompetitive effect, a price increase and output expansion could instead be consistent with the merged firm offering a better product.

4. Examples of natural experiments analysis

This section discusses some specific applications of natural experiment analysis to antitrust cases, investigations, and research. In several instances it compares the natural experiment approach to other economic analyses, illustrating how natural experiments differ from direct effects and other tests that have been used. Most of the natural experiments involve changes over time using a control group (in one form or another) while attempting to further control for other influences that could affect the outcomes of interest. As this discussion illustrates, some of the natural experiments have been more useful than others in addressing the issues of interest.

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34. For a discussion of an example of an event analysis where the results were not economically plausible, see Michael Vita & Laurence Schumann, *The Competitive Effects of Horizontal Mergers in the Hospital Industry: A Closer Look*, 10 J. HEALTH ECON. 359 (1991).

4.1. Price fixing

Economists often perform direct effects analysis in price-fixing cases to estimate damages or address liability issues. These analyses typically compare prices in a market before and after an allegedly anticompetitive event (an alleged agreement to fix prices) to determine if prices increased after the alleged agreement. There can, however, be limitations to this approach.[35] This section first discusses this type of direct effects analysis in some detail and then contrasts it to a natural experiment approach.[36]

Regression analysis frequently is used to control for factors that might influence prices other than the alleged price fixing. At times, this involves estimating an equation for the entire time period (or all geographic areas) with price as the dependent variable, and supply and demand variables as explanatory variables. The equation would explicitly include an indicator variable for the time period of the alleged price fixing (or in the case of differences across geographic areas, the indicator variable would be the areas where the price fixing allegedly occurred). The estimated effect of this indicator variable would be used to measure the impact of the alleged price-fixing behavior.

An alternative approach is to estimate the equation just for the time period or geographic areas without price fixing. This yields estimates of the normal influences of the key supply and demand factors on price. The estimated parameters (quantitative measures of the influences of supply and demand) can then be multiplied by observed values for these explanatory variables during the period of the alleged price fixing to predict what prices would have been absent price fixing. One can then calculate and analyze the differences between actual and predicted values. If the actual values are significantly greater than the predicted values, then one can conclude that the pricing data are consistent with price fixing. If not, these data are inconsistent with the allegation.

Figure 4 provides a hypothetical example in which prices are substantially higher in the price-fixing period than in the non-price-fixing period. The solid line shows actual prices over the entire period. The dashed line shows predicted prices, using an equation estimated from prices in the non-price-fixing period that may not have controlled for all important external influences on prices. Actual prices in the non-price-fixing period are reasonably close to predicted prices (sometimes above and sometimes below as would be expected in any estimation) during the period before the alleged price fixing, but prices in the price-fixing period always are above the predicted levels. This hypothetical also shows that actual prices tend to be more stable in the alleged price-fixing period than in the non-price-fixing period, as one would also expect if there were price fixing.

However, controlling for factors other than the event can be very important. Assume that, in the above example, (1) a significant cost increase occurred at the time of the

35. For example, determining the end of the alleged conspiracy to coincide with a decline in price can cause a bias to finding damages and suggesting a conspiracy. Dennis Carlton and Greg Leonard have suggested an approach to address this problem. *See* Dennis W. Carlton, *Using Economics to Improve Antitrust Policy*, 2004 COLUM. BUS. L. REV. 283, 304-06 (2004).

36. For a more detailed discussion of the two alternative approaches for estimating direct effects, see James Nieberding, *Estimating Overcharges in Antitrust Cases Using a Reduced Form Approach: Methods and Issues*, 9 J. APPLIED ECON. 361 (2006).

alleged price fixing that affected all firms in the market similarly, and (2) the initial estimating equation had not adequately controlled for the influence of this cost increase on prices. A more complete analysis could find that the cost increase resulted in higher predicted prices after the event.[37] Figure 5 replicates Figure 4, except that the predicted prices now reflect the effect of the cost increase on prices. In this case, the actual and predicted prices are relatively close, and the results could not be used to support a conclusion that the alleged price fixing had a substantial impact.

Natural experiments also have been used by economic experts in price-fixing cases to assess damages and in some cases liability issues.[38] A natural experiment in these cases may compare prices over the same period for comparable products where there is no allegation of price fixing. Alternatively, there may be geographic areas affected by the alleged price fixing and geographic areas not affected by the price fixing.

The economic tools in these types of natural experiments are similar to the direct effects analysis described above, but instead primarily use a benchmark product or geographic area to control for other market forces. For this type of natural experiment, the dotted line in Figure 4 would be the comparable product or geographic area, instead of a comparison of prices in the market at issue before and after the alleged conspiracy. Even with a natural experiment, however, one may need to control for differences

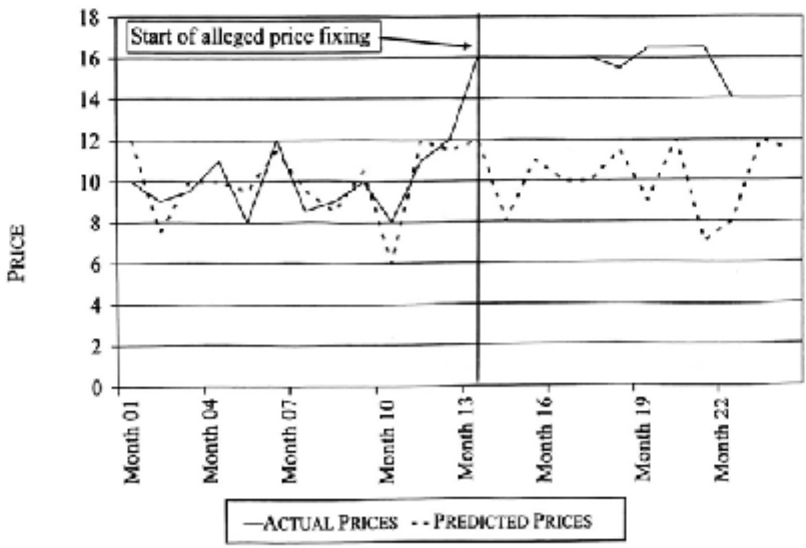

Figure 4.

Case 1—Actual and predicted prices.

37. James Langenfeld has found this in several litigations in which he was involved.

38. ABA SECTION OF ANTITRUST LAW, PROVING ANTITRUST DAMAGES, and ANTITRUST LAW DEVELOPMENTS, *supra* note 3; PRATT, REILLY & SCHWEIHS, *supra* note 3.

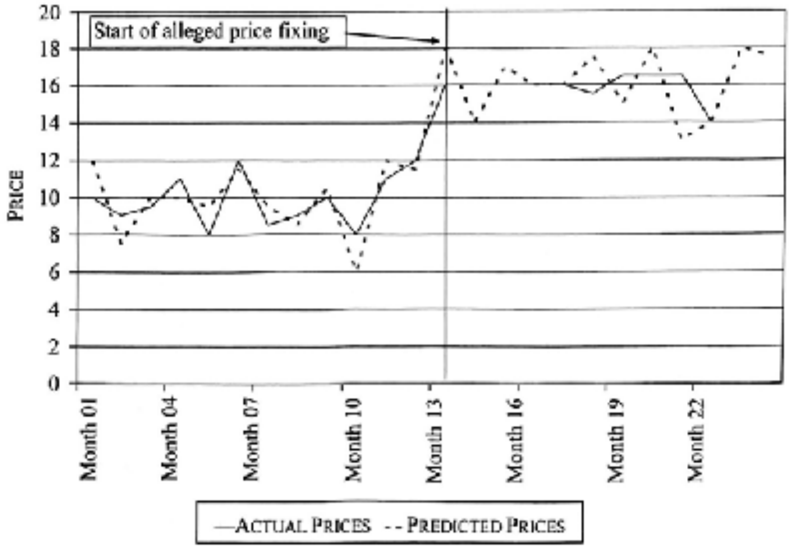

Figure 5.
Case 2—Actual and predicted prices.

between the market at issue and the control group (the benchmark). After controlling for these other factors with a regression analysis, a proper natural experiment analysis also can imply no evidence of conspiracy, as shown in Figure 5. The natural experiment analysis shown in Figure 4 would not have adequately controlled for key market influences and therefore could be subject to a *Daubert* challenge.

Natural experiments can be superior to direct effects tests if the control group's market structure and dynamics are very similar to those of the market at issue, reducing the need to try to model and test all of the possible influences beyond the impact of the alleged improper actions. Natural experiment analysis can also complement direct effects analysis, providing a cross check on the results of direct effects or other forms of analysis.

4.2. Merger retrospectives: Marathon-Ashland joint venture

There have been several merger retrospectives studies, and they may provide natural experiments for evaluating future mergers.[39] As an example, this section focuses on a

39. *See, e.g.*, Michael G. Vita & Seth Sacher, *The Competitive Effects of Not-For-Profit Hospital Mergers: A Case Study*, 49 J. INDUS. ECON. 63 (2001); David M. Barton & Roger Sherman, *The Price Effects of Horizontal Merger: A Case Study*, 33 J. INDUS. ECON. 165 (1984); E. Han Kim & Vijay Singal, *Mergers and Market Power: Evidence from the Airline Industry*, 83 AM. ECON. REV. 549 (1993); LAURENCE SCHUMANN, ROBERT ROGERS & JAMES REITZES, CASE STUDIES OF THE PRICE EFFECTS OF HORIZONTAL MERGERS (FTC Bureau of Economics Staff Report 1992).

study of the impact of the Marathon-Ashland joint venture conducted by FTC economists Christopher T. Hosken and Daniel S. Taylor.[40]

Marathon and Ashland created a joint venture of all their downstream petroleum assets in 1998 (refining, distribution, and marketing). This was the first in a series of significant petroleum mergers and joint ventures in the late 1990s and early 2000s. There were subsequent mergers with similar concentration levels in marketing (wholesale and retail) to the joint venture, in which the FTC challenged and required divestitures. However, the FTC reviewed the Marathon-Ashland joint venture and did not require any divestitures. Hosken and Taylor investigated what happened to prices after the joint venture. They chose one city where the concentration changes were most significant to analyze the effects on pricing.

Several challenges arose in conducting this analysis. First, what prices should be used? This decision is more complex than it may first appear, as there are many different formulations and grades of gasoline in the United States. Accordingly, the authors analyzed several different measures. Another challenge was how to control for other factors. The authors determined that strictly relying on direct controls was not likely to be adequate because data on other factors that might influence prices were not available. Instead, the authors used the control group (benchmark) approach, and selected three different possible control group cities from which to compare prices. As detailed in the paper, another challenge was how to statistically model the analysis given the characteristics of the pricing data that were available. The authors found that retail prices did not increase after the merger. The authors did find a wholesale price increase about 15 months after the merger, but found that this price increase likely was due to a change in supply availability rather than the merger. This analysis is consistent with no adverse competitive effects from the FTC allowing the joint venture.

Hosken and Taylor's analysis of the effect of a previous joint venture was a natural experiment analysis because it was based on a comparison of other areas where the joint venture had little impact. Additionally, their research may provide a natural experiment for evaluating the competitive effects of future joint ventures or mergers in the industry. For their research to be useful in evaluating future joint ventures, the market structure and competitive dynamics of any new joint venture or merger should be very similar to Marathon-Ashland. Also, the nature of competition should not have changed substantially from the period Hosken and Taylor analyzed.

4.3. Impact of market concentration on prices

The Heinz-Beechnut merger. In *FTC v. H.J. Heinz Co.*,[41] the FTC challenged the proposed merger of Heinz and Milnot (which owned Beechnut), the number two and three suppliers of baby food in the United States. The FTC lost its challenge at the district court, but the appeals court overturned the ruling. As in *Staples*, part of the

40. Christopher T. Taylor & Daniel S. Hosken, The Economic Effects of the Marathon-Ashland Joint Venture: The Importance of Industry Supply Shocks and Vertical Market Structure (Federal Trade Comm'n, Working Paper No. 270, 2004). Mary Coleman was Deputy Director for Antitrust at the Bureau of Economics of the FTC at the time of this study.

41. 116 F. Supp. 2d 190 (D.D.C. 2000), *rev'd*, 246 F.3d 708 (D.C. Cir. 2001).

arguments made by the parties in defense of the merger related to Heinz and Beechnut not competing against each other in all areas of the country.[42] Taking advantage of this natural experiment, the defendants' expert (Professor Jonathan Baker) compared retail prices across areas where both competed versus areas where only one of the merging parties competed, attempting to control for other factors that could explain price differences. Baker found that prices were not different when both competed versus when only one competed. He used this result to conclude that competition between Heinz and Beechnut was not important at the retail level. The district court appeared to put some weight on this finding, while the appeals court gave it less weight (focusing instead on the competition between Heinz and Beechnut to get on the shelves and the general structural conditions in the industry).

The Princess-Carnival merger. During 2002, the FTC investigated the proposed mergers of Princess with either Royal Caribbean or Carnival and ultimately chose not to challenge either deal.[43] As part of this analysis, the FTC assessed whether differences in the number of competitors across geographic areas (or "trades") resulted in different prices. Regressions were run estimating the relationship between pricing and concentration using annual observations by geographic area and controlling for other factors, including area-specific dummy variables and variables controlling for changes in demand. The FTC also considered whether ships in certain trades with higher concentration were more "profitable" than ships in other trades. These studies showed no systematic relationship between concentration and price or profitability. The studies, however, highlighted the difficulties that can be encountered in comparing market structures in different geographic areas. Controlling for other factors potentially affecting each trade was difficult, and, thus, these analyses were at best crude tests. These analyses could not be seen as clearly satisfying the *Daubert* requirement of adequately controlling for other factors or being robust. Under any condition, these analyses did not find evidence indicating that the number of competitors mattered, which was consistent with other qualitative and quantitative evidence.

The Aloha-Trustreet merger. Aloha agreed to purchase Trustreet's one half share of their jointly owned gasoline terminal and the operation of Trustreet's gas stations on Oahu.[44] In its complaint,[45] the FTC argued that the relevant market was the "marketing of gasoline by bulk suppliers." In this market, the FTC claimed there were two import capable gasoline terminals (one jointly owned by Aloha and Trustreet, and one owned by Shell). Over time, Texaco, BC Oil, and then Trustreet operated the half of the joint

42. Gerber, the leading supplier of baby food, competed in all areas.

43. For a more detailed discussion of the empirical analyses conducted in this investigation, see Mary Coleman, David Meyer & David Scheffman, *Empirical Analyses of Potential Competitive Effects of a Horizontal Merger: The FTC's Cruise Ships Mergers Investigation*, 23 REV. INDUS. ORG. 121 (2003). Mary Coleman worked on these mergers while at the FTC, and James Langenfeld was engaged by one of the parties.

44. *See* Press Release, Federal Trade Commission, Federal Trade Commission to Challenge Aloha Petroleum Ltd.'s Planned Purchase of Hawaiian Gasoline Assets of Trustreet Properties, Inc. (July 28, 2005). James Langenfeld was the economic expert engaged by the merging parties. Dr. James Nieberding also was involved in and substantially contributed to this work.

45. Complaint for Temporary Restraining Order and Permanent Injunction at 7:14-16, FTC v. Aloha Petroleum and Trustreet Properties, CV05 00471 HG KSC (D. Haw. filed July 27, 2005).

terminal that Aloha did not own. In addition, the FTC included two refiners of oil on Oahu (Chevron and Tesoro) in the same bulk supply market. The FTC challenged the merger, alleging it would (1) reduce the number of independent bulk gasoline suppliers from five to four and (2) reduce competition at the retail level on Oahu. The key evidence presented by the FTC in a temporary restraining order hearing was its economic expert's natural experiment analysis, which predicted that reducing bulk suppliers from five to four would raise retail prices in Hawaii by $0.16. After the temporary restraining order hearing, the local newspapers highlighted this predicted price increase. Aloha agreed to provide a local retailer access to the terminal just prior to trial, and the FTC dropped its challenge without a consent order.[46]

The FTC economist presented graphs and econometric analyses of what he believed to be natural experiments that showed a price increase with four instead of five bulk suppliers. In particular, he focused on Department of Energy prices, analyzing: (1) Hawaii/U.S. (mainland) retail price differences; (2) Hawaii/U.S. (mainland) wholesale price differences; (3) retail Hawaii prices; and (4) wholesale Hawaii prices. His analyses divided these price series into five periods since 1994, as follows:

- base period (1994 to July 1997),
- period 1: Texaco divestiture period for half of the jointly owned terminal (July 1997 to March 1999),
- period 2: BC Oil initially operates half of terminal (March 1999 to August 2000),
- period 3: BC Oil bankruptcy (August 2000 to January 2002), and
- period 4: Trustreet operates half of terminal (January 2002 to January 2005).

The base period presumably was chosen to capture the period before the joint terminal was expanded and became more import capable. The FTC expert claimed that the Texaco divestiture (period 1) and BC Oil bankruptcy (period 3) provide natural experiments of when only four bulk suppliers actively competed. He presented graphical and econometric analyses based on the difference in Hawaii and mainland U.S. retail prices, and his predicted prices for time periods with five and four competitors.[47] His graphical "margin" analysis was in effect a control group or benchmark type of analysis of price differences between different geographic areas, and it did appear to show higher differences in Hawaii/mainland U.S. prices during certain periods of time that roughly corresponded with his four periods, as can be seen in Figure 6.

The FTC expert's econometric analyses used the mainland U.S. prices as a benchmark but also attempted to control for other influences on prices in Hawaii (e.g., the number of tourists as a measure of the level of demand for gasoline). There was a great deal of disagreement between the opposing experts about whether this analysis was an appropriate natural experiment and, even if it were, whether the analysis reliably predicted a price increase during the periods of allegedly fewer competitors.

46. *See* Press Release, Federal Trade Commission, FTC Resolves Aloha Petroleum Litigation (Sept. 6, 2005).

47. The FTC expert performed similar analyses of the difference between Hawaiian and mainland U.S. wholesale prices.

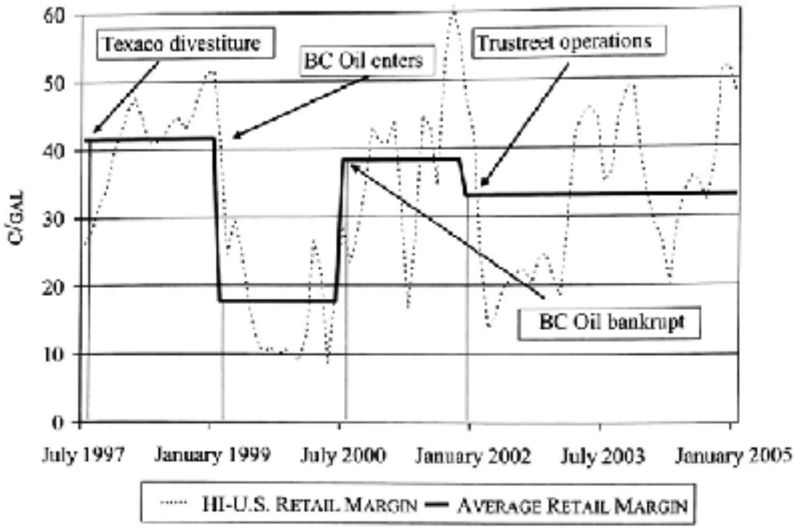

Figure 6.

Dr. Hayes's analysis of Hawaii-U.S. retail margins.

There was a basic disagreement about whether the experiments fit the facts of the case. First, there were always five competitors throughout the four time periods, never four. There was virtually no evidence indicating that Texaco did not compete during the divestiture period. Moreover, BC Oil went bankrupt, so was not a sustainable competitor even if its entry did temporarily force prices down. BC Oil did not pay taxes or many of its bills. BC Oil's unpaid taxes alone were over $0.16 per gallon, the same fall in prices as estimated by the FTC economist. BC Oil also had high cost of gas, not an "import parity" price that the FTC alleged was the key in establishing an independent bulk supplier.

Second, the FTC economist's result depended entirely on changes in mainland U.S. gas prices, not changes in Hawaiian prices. Average Hawaiian prices were roughly the same before and during the "Texaco divestiture" period, as well as during the "BC Oil entry" period, as can be seen in Figure 7 below.

Hawaiian prices did begin to increase; however, the price changes did not occur at the times posited by the FTC expert. The increase in Hawaiian prices occurred during the initial period when BC Oil operated Texaco's portion of the terminal, when the FTC expert claimed there was an increase in the number of competitors from four to five, and six months before the BC Oil bankruptcy period that was claimed to have only four competitors. In addition, Hawaiian prices begin to fall three months before Trustreet Operations when it was claimed five firms competed, instead falling during the period of BC Oil's bankruptcy when its was claimed that there were only four competitors.

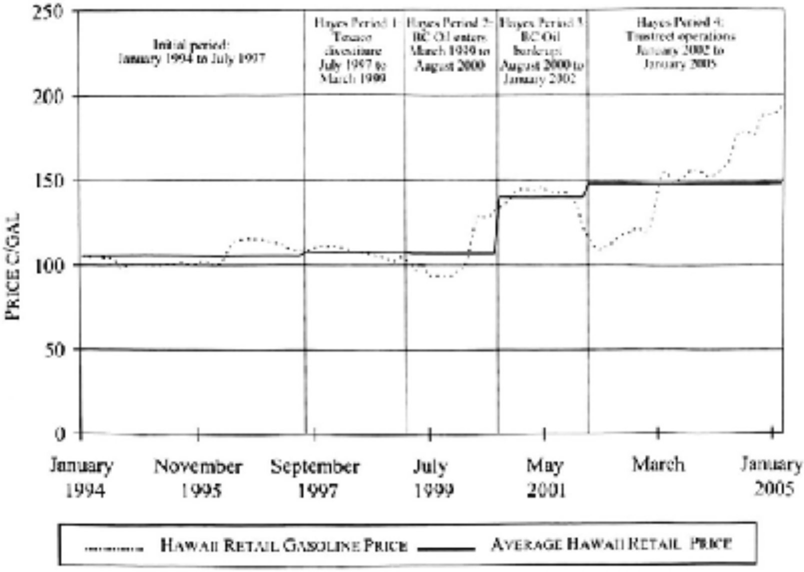

Figure 7.

Dr. Hayes's data—Hawaii actual retail and actual wholesale prices.

Third, there was substantial evidence that prices in mainland United States do not contemporaneously determine prices in Hawaii, and so the contemporaneous comparisons of mainland U.S. and Hawaiian prices were not reliable. Documentary and econometric evidence show prices in Hawaii lag mainland U.S. oil prices. For the most part, Hawaii received its supplies of gasoline and oil from sources outside the United States, and often the cost of the shipments was determined before the gasoline was shipped rather than when it was received on the islands. Mainland U.S. prices reflected local supply and demand conditions, including both locally produced and imported gasoline and oil. Although the gasoline markets in Hawaii and mainland United States were ultimately influenced by world supply and demand considerations, the adjustment times were not simultaneous—and market participants explicitly realized this in their regular business analyses of Hawaiian prices. Making this adjustment changed the econometric results, as discussed below.

There also was disagreement about whether the econometric analysis adequately controlled for other influences on price, as well as whether the econometric model was correctly specified. From analyses by market participants in their normal course of business and econometric tests, there was substantial evidence that lagged U.S. oil prices were more appropriate to use than contemporaneous U.S. gasoline prices. In addition, the FTC expert's analysis did not explicitly control for the impact of other important market factors in Hawaii on prices, such as the expansion of hypermarkets (Costco) and Aloha increasingly offering favorable gas prices and expanding sales.

Finally, there were questions about the robustness of the FTC expert's results. Many specifications that took into account market dynamics and the lagged effect of U.S. oil prices on Hawaii made the FTC's econometric results go away. Moreover, other market evidence was inconsistent with the FTC economist's results. For example, more gasoline was sold by Texaco during the divestiture period than by BC Oil or Trustreet during the competitive periods, implying more competition in a period with allegedly fewer competitors. Also, the FTC economist's econometric results indicated that expansion of the jointly owned terminal increased prices, rather than reduced them, which is inconsistent with arguing that the terminal's capacity created price competition.

In sum, there was a great deal of disagreement about the reliability of the natural experiment that was a central part of the FTC's case, and these disagreements went directly to several of the basic *Daubert* requirements—including that the experiment adequately fit the facts of the case, allowed reasonable inferences about the merger, adequately controlled for other factors, and was robust and economically reasonable. It is unclear how a court would have evaluated and weighed these substantive disagreements if this case had been litigated, or if there could have been a successful *Daubert* challenge, but it is clear that the natural experiment analyses were a major focus of the case.

4.4. Evaluating the strength of a competitor

One way to evaluate the past and prospective strength of one of the parties to a merger is to analyze a past change in its competitive strategy. Consider the following stylized merger, based on an actual case.[48] One of the merging parties (firm A) has a very high share in the relevant market, and several other firms—including the other merging party (firm B)—have relatively small shares. No firm other than firm A has truly national coverage. Firm B also has a well-known brand in a related product area. Firm B seeks to purchase firm A. A few years before the proposed merger, firm B made a substantial effort to gain market share. This event (firm B's changed competitive strategy) might be used to assess whether firm B is competitively important in the relevant overlapping market.

To assess this issue, one can measure what happened to firm B's share with its changed strategy, how (if at all) firm A reacted, and whether firm B's actions are likely to be sustained or repeated in the future. Assume that the results are as follows. Firm B gained substantial share initially by getting shelf space and firm A initially reacted by increasing somewhat its promotional spending. If such outcomes had been sustained, one might consider this evidence of firm B's competitive significance (particularly given the relative lack of evidence of competition from other firms). As shown in Figure 8, firm B quickly lost its share gains (because it lost shelf space) and reverted to its previous strategy. Firm B's share was lower than when it began this strategy. Firm A also reverted to its previous strategy. These outcomes suggest that firm B's impact was short lived, and there is some question as to whether such an event would be repeated because it was costly to gain shelf space with only a short-term gain. The event

48. Mary Coleman was Deputy Director for Antitrust at the Bureau of Economics of the FTC at the time of this analysis by the FTC.

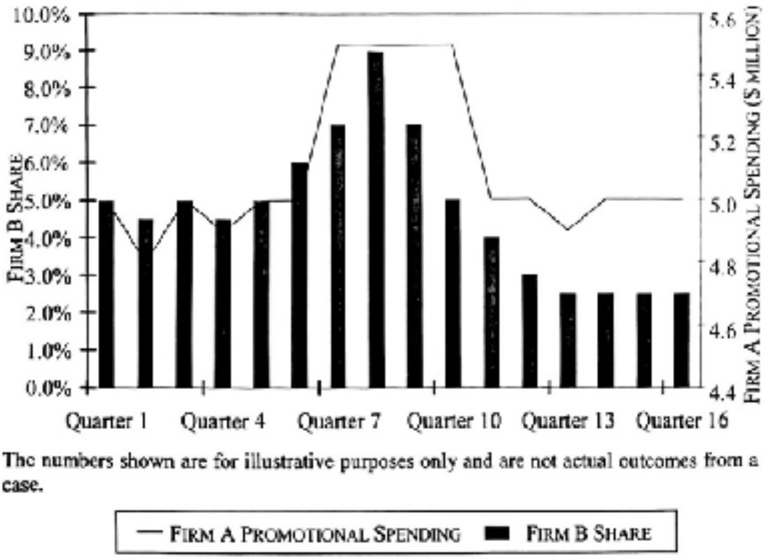

Figure 8.

Impact of Firm B changed strategy on Firm B share and Firm A promotional spending.

provides some evidence of past competitive interaction, but it is not clear as to the inference with regard to future competitive interaction. Thus, this natural experiment only had limited usefulness in assessing the potential competitive effects of the merger, in part because it did not clearly meet the *Daubert* requirement of adequately fitting the facts of the case.

4.5. *Market definition*

Product market: Princess-Carnival merger. A key issue in the matters involving the merger of Princess with either Carnival or Royal Caribbean was market definition.[49] As part of that analysis, the FTC considered the elasticity of the demand for cruising. Cruising is a very complex industry with prices that vary across types of accommodations, itinerary, type of ship, and other factors. In addition, prices for any particular type of cabin on any specific cruise vary significantly over the booking cycle, which is about 18 months. Thus, estimating demand elasticities is problematic.

However, the FTC had the advantage that, during the period of the data, there was a very large increase of capacity in a short time during 2000 and 2001. The FTC used this natural experiment to develop some crude estimates of demand elasticity. This natural

49. Again, note that Mary Coleman worked on the proposed Princess-Carnival and Princess-Royal Caribbean mergers while at the FTC, and James Langenfeld was engaged by one of the parties.

experiment provided striking evidence—the industry absorbed this large short-run increase in capacity with very little impact on capacity utilization and a very modest effect on the level of prices. This outcome was accomplished, in part, through use of yield management. But the result was still striking. That the cruise industry could absorb this capacity so readily with only a modest reduction in price levels is consistent with demand for cruise vacations being very elastic and, thus, with the conclusion that cruise vacations would be part of a broader vacation market if there were an across-the-board price increase.[50]

The FTC estimated arc elasticities of demand (response of average revenue to the large short-run change in quantity) in several different ways. One approach was to estimate an arc elasticity using the percentage change in the average price per day in each year of the natural experiment,[51] and another was to estimate the demand elasticity using regressions controlling for various factors. The estimates of arc elasticity of demand based on this natural experiment were about –2 or greater (in absolute value) for various measures of price and for various specifications. These results, combined with information on margins earned by cruise lines, did not support a cruises-only market based on an across-the-board price increase.

These natural experiment analyses were relatively crude because they did not attempt to control for many other factors that could affect price and so could fail that aspect of the *Daubert* requirements. The FTC staff did attempt to assess whether the years in question were particularly high demand years for vacations. This analysis showed that vacation demand was not particularly high in the years in question and, thus, that factor could not explain the relatively small price decline with the substantial increase in capacity. However, because the analysis was limited in its ability to control for other factors, it was not decisive but did provide one part of the evidence supporting the conclusion on market definition. The FTC found that a cruises-only market could be sustained in the short run for selective price increases because of the use of yield management.[52]

Geographic market: Acetex-Celanese merger. Celanese acquired Acetex, but the acquisition was carefully reviewed by the European Union (EU) before it was allowed to proceed. There were competitive overlaps in the EU for three major chemicals: vinyl acetate monomer (VAM), acetic acid, and acetic anhydride. The key question was whether the geographic markets for these products were limited to the EU, world-wide, or somewhere in between.

Based on the types of analyses that the EU had relied upon in the past, several economic analyses were initially submitted to the EU. One involved a static analysis of

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50. This analysis still left open the question of whether a cruises-only market could be supported based on price discrimination.

51. For a more detailed discussion of these analyses, see Coleman, Meyer & Scheffman, *supra* note 43.

52. *See* Statement of the Federal Trade Commission Concerning Royal Caribbean Cruises, Ltd./P&O Princess Cruises plc and Carnival Corporation/P&O Princess Cruises plc (FTC File No. 021 0041). The FTC did not explain in detail its reasoning. For an analysis of how yield management can lead to a cruise vacation market, see James Langenfeld & Wenqing Li, *Price Discrimination and the Cruise Line Industry: Implications for Market Definition, Competition, and Consumer Welfare*, INT'L J. ECON. BUS. (forthcoming 2008).

existing trade flows. All three products are homogeneous, and there was substantial world trade (e.g., imports accounted for 20 percent of VAM consumption in the EU). The United States was the key exporter for VAM, sending product to both the EU and Asia. This level of existing trade had in the past been taken as indication of a world market.

A second type of analysis that the EU relied on in the past was price correlations. Detailed graphical and statistical analyses were submitted and showed prices highly correlated between regions, even controlling for common costs, as can be seen in Figure 9 for VAM. This figure shows the pricing of VAM over time for the EU, United States, and Asia. Despite the EU's past decisions, the pricing analyses and level of imports did not convince the EU economists that the relevant market was global, and the EU decided to rely heavily on the recommendations of its economists.

Natural experiment analyses were then submitted and substantially contributed to the EU's decision not to challenge the merger.[53] The economists working with the parties tested whether any attempt at a price increase in the EU would induce substantial imports into the EU. For example, there were many cross-overs of prices in different regions, which suggest that prices may diverge but return to comparable levels. The Asian financial crisis of September 1998 lowered Asian demand and prices relative to North America and the EU but returned to similar price levels by October 1999.

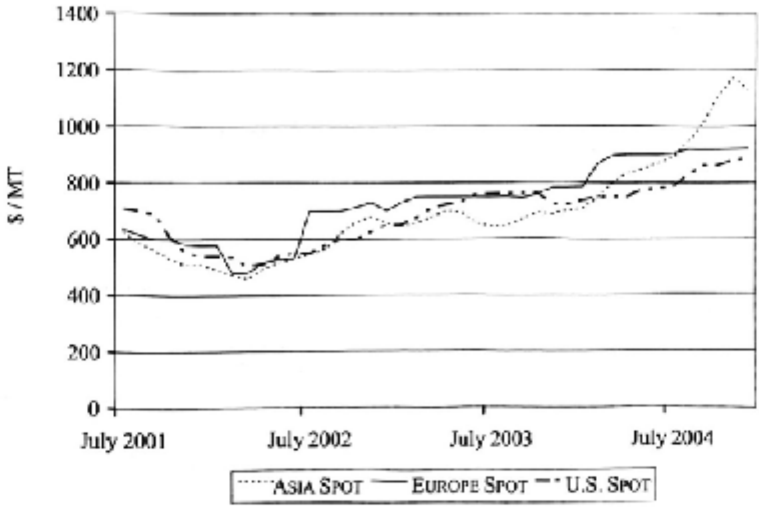

Figure 9.

Comparison of VAM price trends across regions.
ICIS spot price data, 2001–2004.

53. Mary Coleman and James Langenfeld were engaged by the merging parties in this matter. Professor Jerry Hausman and Dr. James Nieberding were also involved and led this work.

Of more importance, there were several econometric analyses of the impact of unexpected plant outages on prices and trade flows. Unexpected outages directly test whether a reduction in output in the EU by a hypothetical monopolist (to increase prices after the merger) would be quickly eroded by substantial imports into the EU from other regions. These outages were particularly good experiments because they were not caused by the competitive give-and-take in the regions. Accordingly, they were similar to an increase in pricing and import response caused by an exogenous change in the market, such as a merger. Many specifications of econometric models estimated impact of outages on prices and trade flows for North America, the EU, and Asia as the data permitted. These analyses consistently showed substantial increases in relative imports and similar price increases in other regions when there were unanticipated outages. For example, econometric analysis found that the ratio of EU to Asian imports from North America significantly increased with EU outages and significantly fell with Asian outages, indicating that North American suppliers shifted supply to the regions where there was a shortage of local supply. Additionally, econometric analysis showed that prices increased in the EU over a three-month period after there were unanticipated outages in either the EU or Asia, suggesting that outages had a similar effect on price in the EU regardless of where in the world they occurred. These analyses were consistent with a global market, in which imports would quickly increase if there were a shortage and local prices increased. In effect, the EU evaluated these natural experiments by applying most of the *Daubert* requirements, such as finding that the data and techniques were reliable and that the experiments adequately fit the relevant facts for market definition. Further analyses could have attempted to draw inferences as to the relevant elasticities and directly link them to the EU's test for market definition.[54] However, the EU closed its investigation without requiring this test, presumably because it found the substantial changes in trade flows due to outages sufficient to show a world market in the context of the other evidence.

5. Conclusion

Natural experiments can provide a useful tool to assess competitive effects in antitrust cases, as well as key aspects of structural analyses such as market definition and entry. However, as with other empirical analyses, to add value such analyses must be grounded in the particular facts of the case and employ sound economic methodologies. In particular, the experiment should provide a reasonable approximation of the competitive behavior of concern, employ techniques that can reasonably measure outcomes, control for factors other than the event that might explain changes in outcomes, be robust across economically reasonable alternative analyses and techniques, and be consistent with other important economic implications of the theory of the case and the market dynamics.

54. *See* Commission Notice on the definition of the relevant market for the purposes of Community competition law, 1997 O.J. (C 372) 5.